The appropriateness of ISDA SIMM™ for delta risk initial margin calculations in the South African over-the-counter interest rate swap market

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ABSTRACT

This research assignment assesses the appropriateness of the calibrations in the ISDA SIMM for calculating delta risk initial margin (IM) in the current over-the-counter interest rate swap market in South Africa. Three main experiments are conducted that include novel ways of delineating and uncovering potential risks in the ISDA SIMM. By comparing the delta risk IM obtained using the standard model and that of a filtered historical simulation expected shortfall model that is calibrated to the South African swaps index curve, the IM appropriateness can be inspected for various profiles based on their relative sensitivities to the tenors of the swap curve. The experiments show that the ISDA SIMM is appropriate in most cases, but due to its broad calibrations, some shortfalls are shown to exist. The results are standardised throughout and are independent of absolute size, as liquidity and concentration features are deliberately excluded. This makes the results more generally applicable and also makes all the results obtained in the analyses comparable. The framework developed here can be replicated by practitioners using their own systems in order to obtain results that meet their internal calibrations as well as their specific risk and return requirements.

Key words:

ISDA SIMM; initial margin; interest rate swaps; filtered historical simulation; expected shortfall; over-the-counter

OPSOMMING

Hierdie navorsingsopdrag beoordeel die toepaslikheid van die kalibrasies in die ISDA SIMM vir die berekening van die aanvangsmarge (AM) van die delta-risiko in die huidige oor-die-toonbank rentekoersruilkontrakmark in Suid-Afrika. Drie hoofeksperimente word uitgevoer wat nuwe maniere insluit om potensiële risiko's in die ISDA SIMM te ondek en te omlyn. Deur die AM van die delta-risiko wat met die standaardmodel verkry word, te vergelyk met die van 'n gefiltreerde historiese simulasie-verwagte tekortmodel wat gekalibreer is deur die Suid-Afrikaanse uitruilkontrakindekskurwe te gebruik, kan die toepaslikheid van die AM ondersoek word vir verskillende profiele op grond van hul relatiewe sensitiwiteit vir die tenore van die ruilkurwe. Die eksperimente toon dat die ISDA SIMM in die meeste gevalle toepaslik is, maar daar is blykbaar 'n aantal tekortkominge as gevolg van die breë kalibrasies. Die resultate word deurgaans gestandaardiseer en is onafhanklik van die absolute grootte, aangesien likiditeits- en konsentrasie-kenmerke doelbewus uitgesluit word. Dit maak die resultate meer algemeen toepaslik en maak ook al die resultate wat in die ontledings verkry is, vergelykbaar. Die raamwerk wat hier ontwikkel word, kan herhaal word deur praktisyns wat hul eie stelsels gebruik om resultate te verkry wat voldoen aan hul interne kalibrasies, sowel as hul spesifieke risiko- en opbrengsvereistes.

Sleutelwoorde:

ISDA SIMM, aanvanklike marge, rentekoersruilkoerse, gefilterde historiese simulasie, verwagte tekortmodel, oor-die-toonbank.

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LIST OF ABBREVIATIONS AND/OR ACRONYMS

BCBS	Basel Committee on Banking Supervision
CCP	Central Clearing Party
ES	Expected Shortfall
EWMA	Exponentially Weighted Moving Average
FHS	Filtered Historical Simulation
FX	Foreign Exchange
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
IRS	Interest Rate Swap
ISDA	International Swaps and Derivatives Association
JIBAR	Johannesburg Inter-bank Average Rate
LIBOR	London Inter-bank Offered Rate
LO	Long Only
LS	Long Short
LT	Long Term
MPR	Margin Period of Risk
MTM	Mark-to-Market
OTC	Over-the-Counter
PAY	Paying Floating Swap
PV	Present Value
PV01	Present Value of a Basis Point
REC	Receive Floating Swap
SA	South Africa
SABOR	South African Benchmark Overnight Rate

SBA	Sensitivities Based Approach
SIMM	Standard Initial Margin Model
SO	Short Only
ST	Short Term
UK	United Kingdom
VaR	Value-at-Risk
VM	Variation Margin

CHAPTER 1

INTRODUCTION

Initial margin (IM) is the extra collateral that is usually paid upfront at the start of a transaction which is independent of the mark-to-market (MTM) value of any party's exposure to the trade. Its aim is to cover the close-out costs related to a counterparty default on an over-the-counter (OTC) derivative. The ISDA SIMM™ is the industry standard for calculating IM in the uncleared OTC markets (ISDA, 2017*a*). The International Swaps and Derivatives Association (ISDA) standard initial margin model (SIMM) brings much needed market consensus to IM calculation, with a methodology that is easy to use, yields quick results and does not require calibration on the users' part. ISDA performs the calibrations, and reviews them quarterly, where three years of the most recent data and one year of stress is used to calibrate the parameters in the SIMM. By focusing the analysis to only South African (SA) interest rate swap (IRS) type portfolios, a few of the SIMM parameters can be isolated and tests can be conducted on their appropriateness in this market by stressing the input space of the model.

The SIMM at the time of writing is version 2.3 released on 1 September 2020 and is required to be implemented by 1 January 2021 (ISDA, 2020*b*). This analysis primarily aims to evaluate the IM appropriateness of the ISDA SIMM in the SA IRS market. This is done by comparing the SIMM IM requirements against various risk calibrations of an expected shortfall (ES) filtered historical simulation (FHS) model, that is traditionally used to calculate IM. This model is calibrated to the SA swap curve index and scaled to current volatility levels (at the time of writing). Three types of analysis are performed that give results that allow for a thorough understanding of the sources of potential misspecification of the SIMM calibrations. These novel ways utilise principles in model risk verification to assess the risks within the SIMM. These experiments essentially measure the "gaps" in "gap risk" coverage.

The analysis also aims to uncover for which key profiles the ISDA SIMM shows to have inadequate risk coverage in comparison to the FHS ES model at the 10-day 99% level in particular. Various simple and novel techniques are applied to identify the sources of risk. The three analysis are termed: isolated tenor comparisons, standardised comparison and randomised portfolio comparisons. This has the potential to show which of the broad calibrations of the SIMM lead to inadequate delta risk

IM coverage. The analysis standardises the results to be independent of the size of the exposures and excludes liquidity features so that the results can be universally applied. This standardisation allows for a focus on the relative sizes of the portfolio exposures rather than on absolute size. This makes comparison across experiments possible and also allows the results to be applied by a broad range of practitioners. The framework that is developed can be replicated by practitioners using their own systems to obtain results that are more consistent with their own internal calibrations and more suitable to their own specific risk requirements.

This research assignment is set out as follows. A literature review in chapter 2 is necessary to acquire the tools to perform and understand the analysis. Then a detailed methodology is laid out in chapter 3 that sets up three main experiments that aim to analyse the components of SIMM by comparing them to ES estimates from the FHS model. A validation procedure is also given to justify the results that are obtained in chapter 4. This chapter discusses and analyses the results obtained by employing the methodology. These findings show that the SIMM is more than adequate in most cases, however there are some fringe cases that breach the SIMM at the required calibration. This research assignment concludes in chapter 5 where the findings of this research are discussed. Recommendations on how the results should be applied in practice and recommendations on how to use this framework for assessing appropriateness of the delta risk in SIMM are given. Further recommendations are given on how to conduct extended research utilising variations of this framework that could answer some additional questions regarding risks in IM coverage.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter is a literature review of the main topics that are required to understand the analyses conducted in this research assignment. Motivations from literature for the choices made in developing the methodology in chapter 3 is presented. The topics themselves follow sequentially, building on another, leading into a scheme for comparing models and evaluating the risks in the SIMM.

In order to understand what SIMM is, or IM for that matter, first an understating of how swaps work and how collateral plays a role in counterparty risk mitigation needs establishment. This foundation is given in section 2.2, where the basics of IM and how it relates to the margin-period-of-risk (MPR) is formed. Section 2.3 gives the natural and traditional ways for calculating IM. Section 2.4 introduces the ISDA SIMM which is the universal IM calculator for uncleared OTC derivatives.

Some notes from literature regarding the definitions of model risk is given in section 2.5. Principles of model validation and comparison are also presented in this section with reference to ways that the models in the comparison can be subject to validation. Lastly, section 2.6 briefly summarises the chapter.

2.2 INITIAL MARGIN AND SWAPS

IM is a type of collateral that is posted on centrally cleared and uncleared OTC derivatives. This type of margin is distinct from variation margin (VM) in a number of ways explained in this section. These terms and concepts are defined and discussed in this section. In order to deliver the concepts and to remain relevant to the analysis conducted, IM is explained in the context of IRS.

A swap is a contract between two parties that specifies an agreement for them to exchange cash flows on defined dates in the future. In a domestic OTC swap one party will pay cash flows, on the defined dates, that are linked to a floating rate (in a given currency such as LIBOR) while the other party will pay a cash flow linked to a fixed rate that is decided upon at the outset. The fixed rate is chosen such that the par value (difference between discounted present value of floating cashflows and fixed cashflows) is zero. This makes the trade fair at inception (Hull, 2018).

The market interest rates, that determine the cashflows of a swap, change on a daily basis, therefore as time progresses the floating rates may increase or decrease, thus either decrease or increase the value of the swap in discounted PV terms. This daily difference between the PV of the fixed side versus floating side is called the mark-to-market (MTM) and defines the market risk exposure of the swap. The parties on either side of the swap would have a different sign of the MTM depending on either an increase or decrease in the rates.

Since cash flows are paid on a fairly infrequent basis (monthly, quarterly, semi-annually, annually, etc.), market participants aim to mitigate their exposures by pledging to post collateral at more frequent intervals to cover the MTM on their side and reduce the exposure. This type of collateral is known as variation margin and is only required to be paid by the party that has the negative MTM[1], i.e. the party that has larger PV of liabilities versus PV of expected income. Therefore the exposure for the swap is mitigated, and thus more of the PV of cash-flow payments can be recovered in case the exposed party's counterparty defaults.

There are many legal and operational processes that take place in reality when default occurs. Gregory (2015, 94-95) states that many residuals risks need to be taken account of that collateral can never fully eradicate. An important aspect in this regard is the inherent delay in receiving collateral. This time period between the last successful collateral call and the eventual close-out of all underlying transactions is referred to as the *margin-period-of-risk* (MPR).

Gregory (2015, 95, 247-251) breaks the MPR down into two sub-periods, pre-default and post-default. The pre-default period starts prior to the first failed collateral call, accounting for valuation periods, settlement periods and grace periods related to either receiving collateral late or not at all. The post-default period starts after the first failed collateral call, which includes the aspects relating to unwinding the position[2]. It is often assumed that the MPR is ten days, which is the recommendation of many regulators, however in reality the MPR can either be shorter or much longer, depending on the specifics of the contract and the parties involved. Andersen, Pykhtin and Sokol (2017) have modelled the MPR by looking much closer at the reality of the post-default and pre-default periods for aggressive (parties with strong operational competence) or conservative (en-

[1] Taking into account minimum transfer amounts, thresholds and haircuts discussed in Gregory (2015).

[2] This means all aspects relating to rehedging and replacement of the defaulted transaction including legals fees and transaction costs.

forcement of close-out rights is cautious) calibrations. They have shown that an MPR of seven days for parties with strong operational competence and fifteen days for more conservative calibrations to be realistically appropriate.

IM and and the MPR are closely linked. Once the VM has been posted, ten business days (assumably) would transpire, where the underlying value of the portfolio of transactions could have substantially moved . In order to mitigate the exposure over this MPR, parties pay an upfront collateral aimed at protecting against worst-case losses over this ten day period. This type of collateral is called the IM.

IM is the additional collateral that is required to be posted by both parties irrespective of the sign of their MTM. It is usually required upfront at the trade inception, although it can be subject to more frequent collateral calls. Its aim is to provide an extra "cushion" of safety, known as overcollateralisation, that would cover the adverse risks associated with the aforementioned close out period (MPR) as stated in Gregory (2015, 74). This is to cover the "gap risk" of the portfolio, i.e. the undercollateralisation resulted from the time taken to close the transaction where the PV of the portfolio has deviated from the posted MTM collateral, resulting in a gap between the posted collateral (MTM) and the value of the transaction.

VM and IM are therefore very different with regard to the risks that they aim to cover. The VM, which is required frequently and is comparatively simple to calculate for both the parties involved, essentially amounts to the current MTM[3] value, required to be posted only by the party with the negative MTM. The IM on the other hand aims to cover the worst-possible movements of the portfolio over the MPR, and thus inherently implies forecasting. IM relates to the market risk of the portfolio over the MPR and therefore models that aim to estimate IM have traditionally taken the form of the market models required to calculate capital reserves.

Prior to the introduction of the ISDA SIMM there was no market consensus on the calculation of IM in OTC transactions when not clearing through a CCP other than the rigid SPAN (Standard Portfolio Analysis of Risk) initially introduced by the CME group in the late 1980's (Gregory, 2014, 157)[4]. Strict guidelines had been issued by regulators that specified how the internal IM models

[3]Note that other features are also taken into account such as thresholds, minimum transfer amounts and haircuts that could lead to undercollateralisation regardless (Gregory, 2015).

[4]This legacy methodology is not discussed in this research assignment.

of banks and CCPs should be calculated. Because of the similarity of the underlying market and liquidity risks that IM and regulatory capital models aim to cover, the IM models initially took the form of value-at-risk (VaR) type models. These models would need to be calibrated for a ten day risk horizon at the 99% significance level, essentially aimed at covering the worst possible returns of the portfolio over the MPR.

2.3 TRADITIONAL INITIAL MARGIN MODELS

IM aims to cover the extreme movements of a portfolio's profit and loss over a fixed period of time, which is akin to calculating capital requirements for market risk. IM can therefore be thought of as a VaR metric, meant to cover the delta risks of a portfolio for a particular risk horizon at a given confidence level. This section introduces the idea of various VaR techniques for computing IM and emphasises the techniques traditionally employed by banks and those currently employed by CCPs.

An h-day $\alpha\%$ VaR estimate defines the largest loss that can be generated over a period of h trading days that one is $(1-\alpha)\%$ sure will be exceeded. For example a 10-day 99% VaR estimate of $X\%$ means that one is confident that the loss of the portfolio will not exceed $X\%$ with 99% certainty. Thus for a given portfolio at a certain point in time (t) the VaR can be formally defined, similar to Alexander (2008, 17), as

$$\mathrm{VaR}_{ht,\alpha} = -x_{ht,(1-\alpha)}. \tag{2.1}$$

Where $x_{ht,(1-\alpha)}$ is the $(1-\alpha)\%$ quantile of the portfolio's h-day profit and loss distribution, X_{ht}, so that $P(X_{ht} < x_{ht,(1-\alpha)}) = (1-\alpha)$. The quantile is multiplied by -1, so that the VaR value is in terms of absolute loss.

There are a number of benefits of VaR, which Gregory (2014, 159) outlines before discussing some of its shortcomings. Firstly the metric is favourable since it is relatively easy to interpret, which is evident from the simple definition above. The greatest advantage of the metric is that it does not inherently make assumptions about the underlying profit and loss distribution of the portfolio, although such assumptions can be made to calculate the metric simply[5].

[5]For example making an i.i.d. normal daily return assumption, a simple normal linear VaR estimate follows easily (Alexander, 2008).

Although easy to interpret, the VaR can also easily be misinterpreted. VaR only tells one of the losses one can experience at the given confidence level, and says nothing about the potential losses beyond these bounds. Two distributions may have completely different tail distributions, but could potentially report the same VaR estimate at a given quantile, therefore a more robust and more reliable metric is needed. Secondly, the VaR metric is not coherent, reported in Artzner, Delbaen, Eber and Heath (1999), which in essence means that the VaR metric is not necessarily sub-additive. This is problematic since the individual quantile risk measures on two transactions within the same portfolio combine in unintuitive ways, as the VaR does not easily translate into the sum of the two quantile risks nor does such a sum properly account for the diversification effects within the portfolio.

The expected shortfall (ES) measure, closely related to the VaR metric, can be used to overcome these undesirable properties. The h-day 99% ES is defined as the expected loss of the portfolio profit and loss distribution, X_{ht}, given that the VaR level is exceeded,

$$\mathrm{ES}_{ht,\alpha} = -\mathrm{E}\big(X_{ht} \mid X_{ht} < -x_{ht,(1-\alpha)}\big). \tag{2.2}$$

From this equation one can see how the ES metric relies on the VaR estimate to essentially determine the average worst case losses for the portfolio over an h-day period. Gregory (2014) and Artzner *et al.* (1999) both give demonstrations as to how the shortcomings of VaR are overcome by using this metric using various realistic scenarios. Gregory (2014, 160) shows an example of how the sub-additivity issue is overcome with the ES estimate, as the ES IM requirement of a CCP is less than half for a combination of two portfolios, whereas the same VaR IM requirement would be greater than the sum of the individual VaR estimates. Thus diversification effects are accounted for when using the ES metric for IM requirements.

There are various ways of calculating IM that the CCPs employ, with the most common approaches being historical simulation VaR. Alexander (2008, 141-199) has an entire chapter devoted to historical simulation, where most of the definitions given here can be found. Historical simulation assumes that all possible future variations have already occurred in the past, and therefore the historical return process can be used as a precursor to future profit and loss movements. Apart from this assumption the method does not make any parametric nor distributional assumptions regarding the return process, and is therefore often called non-parametric VaR or ES.

Historical simulation is calculated by taking a long sample period of risk factor returns, relevant to the portfolio in question, and using this as the empirical risk factor return distribution from which the VaR and ES quantile measures can be obtained, after being applied to the portfolio sensitivities. For example, if using a 1000 trading days of historical risk factor returns, the 1-day 99% VaR estimate is simply the 100^{th} largest loss of the portfolios returns, after applying the risk factor sensitivities of the portfolio to the risk factors. The corresponding ES estimate would then amount to taking the average of all the losses larger than the VaR estimate.

The small example above uses a 1-day estimate to explain this concept for a reason. Historical simulation, although convenient and simple to implement on the 1-day return basis, is far more difficult to scale to an h-day estimate as one may suppose. To generate an h-day estimate, one can first obtain the 1-day estimate and scale it up using the *square-root-of-time* rule, but this is prone to lead to inaccuracies (Alexander, 2008, 22, 59, 146). Instead one can use empirical h-day returns to formulate the distribution, however the sample size required to get N h-day samples, will increase directly proportional to h, requiring $N \times (h-1)$ more trading days than the 1-day estimate.

Using too long a historical period, may mean including irrelevant and "old" data, not necessarily relevant to today's market. One may suggest using overlapping h-day samples in order for the h-day samples to coincide with the same period as the 1-day sample, but this has the unfortunate consequence of blunting the tails of the distribution[6], a serious deficit for quantile estimation (Alexander, 2008, 152). These issues, as well as concerns regarding sample size and volatility scaling, can be resolved to a large extent by the filtered historical simulation (FHS) technique.

Filtered historical simulation, introduced by Barone-Adesi, Giannopoulos and Vosper (1999) is a multi-step volatility scaling bootstrap simulation technique. It combines volatility scaling (through GARCH estimation) techniques and historical simulation techniques, in order to create a return distribution reflective of the current market condition. This semi-parametric technique is particularly popular among central clearing parties, such as Eurex (2020)[7], for its ability to scale the historical estimates to be reflective of the current volatility regime.

[6] This also naturally introduces additional auto-correlation to the empirical distribution.
[7] LCH (2020) and CME also use historical simulation with volatility scaling.

Following the financial crises of the past, procyclicality has been a concern with CCPs and CCP regulators. The danger of having a too risk sensitive IM estimate, could lead to higher collateral demands during periods of stress when liquidity to fund these margins are already low (Gregory, 2015, 101). Many CCPs have therefore adopted changes to their methodology to smooth out IM estimates requirements using various techniques, such as margin buffers, including stress periods in their sample and using volatility floors which Gregory (2014, 167) discusses.

With regard to IM for interest rate swaps, there are two main sources of risk, liquidity risk and market risk. This research assignment focuses only on the delta market risk aspect, therefore the liquidity charges that are included in the CCP models are not discussed. The methods employed with regard to IM estimation and liquidity charges differs drastically for different CCPs, with LCH (2020), Eurex (2020) and CME using various historical periods, significance levels (generally around the 99%+ level) and quantile risk metrics (ES or VaR). In order for the model comparison in the subsequent analysis to be fair, a model needs to be chosen that represents the risks of the South African market well. Therefore an FHS ES model is chosen, with the reasons for some of the model choices given in section 3.2.

The ES is a coherent risk measure under the FHS framework as proved by Giannopoulos and Tunaru (2005). This means that the ES metric can be used to obtain robust measures of risk, accounting for the full tail distribution and not suffering from the deficiencies in VaR. This is also consistent from a capital requirement viewpoint for market risk under Basel Committee on Banking Supervision (2019), where ES at the 97.5% percentile for a 10-day horizon is the calibration requirement. The analysis described in chapter 3 and reported in chapter 4, calculate the ES for various risk horizons and quantile levels. The implementation of the FHS methodology follows the lines of Lee and Seo (2018), who have shown the FHS to work in the Korean interest rate market. The FHS algorithm employed for this analysis is given in section 3.2, but a brief general description of how the FHS model works is presented here.

Suppose a portfolio consisting of only one security which is mapped to only a single risk factor. The model requires a robust estimation of the volatility process of the risk factor return process, such as a GARCH or EWMA model. This is required to estimate the daily volatility of each return in the historical sample period. The returns, in this sample period, are standardised, whereby for each trading day the quotient of the daily absolute return and its estimated conditional volatility is returned. This creates a sample of standardised returns which can also be referred to as the residuals. For a given time horizon, say h-days, the algorithm selects h independent random draws from the standardised sample. The conditional volatility on the last day of the sample period is used to initialise the volatility process of the simulation, where the residuals are scaled to have conditional heteroskedastic daily dependence. When using absolute returns, which is the case for these purposes, the estimated h-day return is simply the sum of these h simulations. This can be repeated numerous time, obtaining a bootstrapped sample of historical daily risk factor returns, that can exceed the size of the original sample. The corresponding VaR estimate is minus the $(1-\alpha)$ quantile value of the security return, obtained by applying the risk factor sensitivity to the simulated risk factor returns. The ES estimate is the average of the simulated values above the VaR estimate.

An advantage of the this simulation technique is that it does not require a specification of the complex correlation structures required once more than one security or risk factor is added to the portfolio. This works well for linear portfolios but is particularly useful for non-linear portfolios (Barone-Adesi *et al.*, 1999). As is evident in section 2.4, the delta risk for the SIMM calculation relies heavily on a calibrated correlation matrix.

There are a number of model specifications required for the FHS model, however, such as choice regarding volatility model and sample period. Various assumptions get implied when certain choices are made. Without the presence of a CCP or the choice not to use one, meant many market participants used these complex models in their own internal models (akin to capital VaR models) approach to calculate IM for OTC derivatives in the past. The different model choices have undoubtedly lead to many margin disputes in non-cleared transactions (Gregory, 2015). As a means to limit the number of margin disputes and to decrease global systematic risk, ISDA (2017*a*) introduced the SIMM, a sensitivities based approach to IM calculation that could be globally applied in all financial jurisdictions.

2.4 STANDARDISED INITIAL MARGIN MODEL

In December 2013 ISDA (2013) announced a proposal for an industry standard model that could be used by market participants to calculate their IM requirements for non-cleared OTC transactions. This standard initial margin model (SIMM), aimed at meeting the regulatory BCBS margin requirements, while having several key benefits to the market. These benefits include transparent and timely IM dispute resolutions as well as establishing consistent regulatory governance and oversight.

At this time it was not clear what such a model would eventually look like, but it could be agreed that it needed to meet some important general requirements. The criteria, prescribed in ISDA (2013), which the IM model would need to meet is that it would need to be non-procyclical, with appropriate margins, without creating a cost burden for market participants. The model should also be transparent, predictable and it should be easy and quick to replicate calculations. The model itself needs to be extensible, allowing for modification or additions of risk factors as they become prevalent, as well as having responsible governance between regulators and industry.

The main aim of SIMM is to reduce the systematic risk while maintaining a functional OTC market as well as reduce the number of disputes. It also has various aims at making the IM calculation process more transparent. Following the discussion paper of June 2015 (ISDA, 2015), the SIMM model would need to meet these aims as well as the key criteria. ISDA proposed a sensitivities based approach (SBA) as a methodology for SIMM. This means that IM calculations could be made by applying risk weights and correlations for different assets classes to the portfolio risk factors.

The SBA methodology is intended to be different to the VaR models used by CCPs in IM calculation. There are several reasons behind this, but the most crucial one is that capital models, although based on the same risk mitigation principles, differ substantially from IM (a type of collateral) models in how they are applied in the market. The IM is a counterparty risk mitigation tool that requires collateral to be posted by both parties regardless of the sign of their expected exposures. It would be practically impossible to avoid IM disputes when each participant uses their own internal forecasting models that rely heavily on internal calibrations, proprietary software and licensed data (ISDA, 2016*a*). Each individual IM model would in any case be subject to regulation, making it an expensive procedure. Thus an SBA approach is appropriate in this case, like the standardised approach for capital models. Such an approach would negate the need for data licensing, large calculation costs and allows for easy calculation and replication. The ISDA body would govern and maintain the model and extend it as required by the market. Therefore if the margins under the model prove to be appropriate there would be no need for internal approaches that would individually require regulatory approval.

ISDA (2016*b*) launched the first working version of SIMM on 1 September 2016. By 1 September the following year ISDA (2017*a*) launched ISDA SIMM 2.0, an enhanced version of the original model that included additional risk factors for certain product types. Each year since this initial release (ISDA, 2017*c*), ISDA has released an updated version of this model that has been recalibrated to meet the risk sensitive needs of the most recent times. The most recent updates, versions 2.2 and 2.3, are presented in ISDA (2019) and ISDA (2020*b*) respectively. Version 2.3 is required to be implemented by 1 January 2021.

The ISDA SIMM works as follows. There are four product classes: credit, commodity, equity and interest rates and foreign exchange. The interest rates and foreign exchange (RatesFX, as per ISDA terminology) class is the product class where IRS fall into. It is structured so that each trade is assigned to an individual product class, and SIMM is then considered separately for each product class. These SIMM's can then be aggregated to obtain the total portfolio IM requirement. This aggregation can be done without fear of double counting risks as each product class has its own risk classes.

Within each product class there are six risk classes. Namely interest rate risk, credit risk (qualifying and non-qualifying), equity risk, commodity risk and foreign exchange (FX) risk. The margin for each risk class is defined as the sum of the Delta Margin, the Vega Margin, the Curvature Margin and the Base correlation margin (Base Corr Margin, applicable only in credit qualifying products) i.e.

$$IM_X = DeltaMargin_X + VegaMargin_X + CurvatureMargin_X + BaseCorrMargin_X. \quad (2.3)$$

The total margin for a given product class is then given by

$$SIMM_{product} = \sqrt{\sum_r IM_r^2 + \sum_r \sum_{s \neq r} \psi_{rs} IM_r IM_s}, \quad (2.4)$$

where ψ_{rs} are the correlations between the risk classes. The total SIMM is the sum of the four product class SIMM values:

$$SIMM = SIMM_{RatesFX} + SIMM_{Credit} + SIMM_{Equity} + SIMM_{Commodity}. \tag{2.5}$$

For a portfolio of single-currency IRS one would only consider the SIMM for the RatesFX product class. Specifically since the products are vanilla swaps, the only relevant risk class is the interest rate risk class and the only margin that remains non-zero for this type of portfolio is the delta margin. The formula to calculate SIMM in this case reduces to

$$SIMM = SIMM_{RatesFX} = \text{DeltaMargin}_{\text{Interest rate}}. \tag{2.6}$$

To calculate the delta risk of the interest rate risk class first find the net sensitivity across instruments to each risk factor (k, i), where k is the rate tenor and i is the index of the sub-yield curve. The risk factors for interest rates are defined as the as the yields at the following 12 vertices (k) for each currency: 2 weeks, 1 month, 3 months, 6 months, 1 year, 2 years, 3 years, 5 years, 10 years, 15 years, 20 years and 30 years. The sub-yield curve labels (i) for each currency category are "OIS", "Libor1m", "Libor3m", "Libor6m" and "Libor12m".

The net sensitivity for each risk factor (k, i) is defined as the change in the present value of the portfolio given a basis point increase[8] in the underlying risk factor,

$$s_{k,i} = PV(x_{k,i} + 0.01\%) - PV(x_{k,i}), \tag{2.7}$$

where $PV(x)$ is the value of the instrument given the value of the risk factor x. This definition is often referred to as the present value of a basis point (PV01).

The risk weights, RW_k, for each tenor in tables 2.1 or 2.2 needs to be applied to each of these net sensitivities to obtain weighted sensitivities

$$WS_{k,i} = RW_k s_{k,i} CR_b. \tag{2.8}$$

[8]Note that ISDA allows for participants to use other definitions consistent with their internal systems such as the backward or central difference methods.

The term CR is the concentration risk factor (synonymous with liquidity charges for CCPs) defined for each currency bucket b as,

$$CR_b = \max\left(1, \left(\frac{|\sum_{k,i} s_{k,i}|}{T_b}\right)^{\frac{1}{2}}\right). \tag{2.9}$$

For each currency, b, a concentration threshold, T_b, is specified. This is in order to inflate IM requirements for positions with large absolute exposures in a single currency. This research assignment excludes this liquidity charge, and subsequently does so for the contender model, in order for the results to remain independent of transaction sizes and concentration risks.

Table 2.1: SIMM version 2.2 risk weights.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
Regular currencies	116	106	94	71	59	52	49	51	51	51	54	62
Low-volatility currencies	14	20	10	10	14	20	22	20	20	20	22	27
High-volatility currencies	85	80	79	86	97	102	104	102	103	99	99	100

Table 2.2: SIMM version 2.3 risk weights.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
Regular currencies	114	107	95	71	56	53	50	51	53	50	54	63
Low-volatility currencies	15	21	10	10	11	15	18	19	19	18	20	22
High-volatility curencies	103	96	84	84	89	87	90	89	90	99	100	96

Within each currency the weighted sensitivities are then aggregated to obtain the currency delta margin (K) using the aggregation,

$$K = \sqrt{\sum_{i,k} WS_{k,i}^2 + \sum_{i,k} \sum_{(j,l)\neq(i,k)} \phi_{i,j}\rho_{k,l} WS_{k,i} WS_{l,j}}, \tag{2.10}$$

where $\phi_{i,j}$ are the sub-curve correlations[9]. $\rho_{k,l}$ are the tenor correlations which are fixed for all currency buckets. The calibrated correlations for version 2.2 are given in table 2.3 and the version 2.3 correlations are given in table 2.4. This is the extent of the SIMM IM calculation for the simulated analysis conducted in this research assignment. The simplifications and assumptions are provided in section 3.2.

[9]Fixed at $\phi_{i,j} = 98.5\%$ in version 2.2 and 98.6% in version 2.3.

Table 2.3: SIMM Version 2.2 Interest Rate Risk Correlations.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
2W		0.69	0.64	0.55	0.34	0.21	0.16	0.11	0.06	0.01	0	-0.02
1M	0.69		0.79	0.65	0.5	0.39	0.33	0.26	0.2	0.14	0.11	0.09
3M	0.64	0.79		0.85	0.67	0.53	0.46	0.37	0.29	0.22	0.19	0.16
6M	0.55	0.65	0.85		0.85	0.72	0.65	0.56	0.46	0.38	0.34	0.3
1Y	0.34	0.5	0.67	0.85		0.93	0.88	0.78	0.66	0.6	0.56	0.52
2Y	0.21	0.39	0.53	0.72	0.93		0.98	0.91	0.81	0.75	0.72	0.68
3Y	0.16	0.33	0.46	0.65	0.88	0.98		0.96	0.87	0.83	0.8	0.76
5Y	0.11	0.26	0.37	0.56	0.78	0.91	0.96		0.95	0.92	0.89	0.86
10Y	0.06	0.2	0.29	0.46	0.66	0.81	0.87	0.95		0.98	0.97	0.95
15Y	0.01	0.14	0.22	0.38	0.6	0.75	0.83	0.92	0.98		0.99	0.98
20Y	0	0.11	0.19	0.34	0.56	0.72	0.8	0.89	0.97	0.99		0.99
30Y	-0.02	0.09	0.16	0.3	0.52	0.68	0.76	0.86	0.95	0.98	0.99	

Table 2.4: SIMM Version 2.3 Interest Rate Risk Correlations.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
2W		0.73	0.64	0.57	0.44	0.34	0.29	0.24	0.18	0.13	0.11	0.09
1M	0.73		0.78	0.67	0.50	0.37	0.30	0.24	0.18	0.13	0.11	0.10
3M	0.64	0.78		0.85	0.66	0.52	0.43	0.35	0.27	0.20	0.17	0.17
6M	0.57	0.67	0.85		0.81	0.68	0.59	0.50	0.41	0.35	0.33	0.31
1Y	0.44	0.50	0.66	0.81		0.94	0.85	0.76	0.65	0.59	0.56	0.54
2Y	0.34	0.37	0.52	0.68	0.94		0.95	0.89	0.79	0.75	0.72	0.70
3Y	0.29	0.30	0.43	0.59	0.85	0.95		0.96	0.88	0.83	0.80	0.78
5Y	0.24	0.24	0.35	0.50	0.76	0.89	0.96		0.95	0.91	0.88	0.87
10Y	0.18	0.18	0.27	0.41	0.65	0.79	0.88	0.95		0.97	0.95	0.95
15Y	0.13	0.13	0.20	0.35	0.59	0.75	0.83	0.91	0.97		0.98	0.98
20Y	0.11	0.11	0.17	0.33	0.56	0.72	0.80	0.88	0.95	0.98		0.99
30Y	0.09	0.10	0.17	0.31	0.54	0.70	0.78	0.87	0.95	0.98	0.99	

Delta margins can be obtained by aggregating across currencies,

$$DeltaMargin = \sqrt{\sum_b K_b^2 + \sum_b \sum_{c \neq b} \gamma_{bc} g_{bc} S_b S_c}, \tag{2.11}$$

for specified cross-currency correlations γ_{bc}[10], and where

$$S_b = \max\Bigg(\min\Big(\sum_{i,k} WS_{k,i}, K_b\Big), -K_b\Bigg) \tag{2.12}$$

and

$$g_{bc} = \frac{\min(CR_b, CR_c)}{\max(CR_b, CR_c)}, \tag{2.13}$$

for all currencies b and c. For a single currency the delta margin simply amounts to the K value.

The ISDA (2017*b*) SIMM governance framework specifies that the parameters are calibrated to cover a MPR of ten days at the 99% significance level. This calibration is based on ISDA's own internal data that spans the last three years plus one year of stress, identified as the 2008/9 global financial crisis (ISDA, 2020*a*). ISDA conducts quarterly reviews on shortfall issues regarding the SIMM values. These are based on real market data and reported shortfalls by market participants.

Certain principles from the backtesting procedures in the ISDA (2017*b*) SIMM governance framework are used for developing a comparison scheme, such as the 10-day 99% calibration. In order to evaluate the appropriateness of SIMM in the current SA IRS climate a methodology needs to be developed that targets certain aspects of SIMM and that can help explain some of the shortcomings.

2.5 MODEL VALIDATION

This section addresses the literature regarding model risk and model validation. The aim is to layout a motivation for the analysis conducted and to establish principles for a methodology that would allow for fair comparisons. Some ways of viewing risk in models is presented prior to a discussion on validating models.

In the paper *Model Risk*, Derman (1996) states that all models are ultimately incorrect at some

[10] $\gamma_{bc} = 22\%$ in version 2.2 and 20% in version 2.3.

level. He describes the ways models can go wrong from his experience at Goldman Sachs, where he admits that there is no magic strategy for avoiding model risk. Derman (1996) does note specifically define model risk, but Morini (2011, 3) makes the agreeable statement that model risk is the losses a financial institution could receive due to errors in model development or application. Identifying the errors and understanding their sources form an important part of model risk management.

Derman (1996) provides general guidelines for avoiding model risk, the two most relevant in this case being *test complex models in simple cases first* and *test the model's boundaries*. The former means to test the model against simple known solutions and the latter means to test whether the model makes sense at the extremes. These are the principles used for model comparison which ties into the scheme for model validation presented by Morini (2011, 54-58).

In terms of market intelligence the SIMM is the universal IM calculator for OTC derivatives. This means that the only alternatives to SIMM is to clear through a CCP, or two parties can agree on their own models for IM[11]. A comparison of the traditional IM calculations, that CCP's currently use, with the SIMM will give an indication of the relative risk coverage that SIMM obtains in comparison to a VaR type model.

Since there is no functioning CCP in SA for OTC swaps, a comparison of CCP values with SIMM values that was done for normal-volatility and low-volatility currencies by Barnes (2016) would be impossible. This is however the study that would be necessary in order to evaluate the adequacy and margin appropriateness of the SIMM calibrations for the South African swap market (high-volatility currency). Therefore a model would need to be developed in order to make this comparison.

Using a more complex model, such as a non-parametric historical simulation model, to compare to the SIMM would naturally introduce certain assumptions and model choices. Therefore the comparative model would need to be built on grounds that would make the comparison fair. For this reason aspects of the model verification and model validation steps, such as the choice of vertices in the SIMM, in Morini (2011) are acknowledged but not the aims of this study. This is in order to focus the study rather on the appropriateness of the SIMM calibrations at the given vertices. The comparative model would therefore also require to have the same structure for clear dissemination of the risks.

[11]It would be more likely for parties to apply a multiplier to SIMM IM if it were inadequate than for parties to use their own model for the plethora of reasons given in section 2.4.

The comparison in Barnes (2016) uses isolated exposures for the 2Y, 10Y and 30Y tenors to compare the IM requirements of SIMM and the two CCP's, LCH and CME. Their analysis is standardised, by dividing through by the PV01 exposure, and thereby allowing for a maturity-agnostic comparison across tenors. This also allows averages to be taken so that general statements regarding the average coverage of SIMM can be made. Using features presented in this article an adapted study can be made to assess the margin appropriateness of SIMM in a domestic high-volatility currency scenario.

Since a comparative model is introduced, it would need to be verified in some way. Since the traditional models are VaR type models it would be appropriate to validate them using the same backtesting principles as market risk models. The requirements for market risk risk models is a simple backtesting methodology based on the 1-day VaR at the 99% level over the most recent 250 trading day period. The justification for the various VaR backtesting methodologies is well summarised in Daniel Rösch (2014, 344-355). Performing the *traffic light* backtest method, and achieving a "green" light would indicate that the model performs as intended.

This regulatory backtest is an out of sample statistical backtest. The relevant hypothesis can be formulated by first defining the indicator variable

$$I_{\alpha,t+h} = \begin{cases} 1, & \text{if } Y_{t+h} < -VaR_{ht,\alpha} \\ 0, & \text{otherwise,} \end{cases} \tag{2.14}$$

where Y_{t+h} is the empirical h-day return and $VaR_{ht,\alpha}$ is the h-day α VaR estimate at time t. Note that this indicator is an independent identically distributed (i.i.d.) Bernoulli random variable with parameter α,

$$\{I_{\alpha,t+h}\} \sim \text{bern}(\alpha).$$

Next define the number of success, $X_{n,\alpha}$, as the sum of n of these indicators. This means that $X_{n,\alpha} \sim \text{binom}(n, \alpha)$, is distributed binomially with parameters n and α, hence

$$E[X_{n,\alpha}] = n\alpha, \tag{2.15}$$

and

$$V(X_{n,\alpha}) = n\alpha(1-\alpha). \tag{2.16}$$

The hypothesis can then be formulated as

$$H_0 : \text{VaR model is accurate}, \tag{2.17}$$

which is rejected at the 95% confidence level if the value obtained for $X_{n,\alpha}$ lies outside the approximate interval

$$\Big(n\alpha - 1.96\sqrt{n\alpha(1-\alpha)},\ n\alpha + 1.96\sqrt{n\alpha(1-\alpha)}\Big). \tag{2.18}$$

In other words the model is rejected when the number of exceedances is beyond the number of expected exceedances of the specified VaR model within reasonable confidence bounds. For the regulatory backtests the parameters $n = 250$ and $\alpha = 99\%$ correspond to the interval

$$\Big(-0.5834,\ 5.5834\Big). \tag{2.19}$$

Therefore, statistically, if six or more exceedances are observed, then the VaR model is rejected. The Basel Committee on Banking Supervision (2019) draws the line for the “green zone" at four or less. The model falls within the “amber" zone when thera are between five and nine exceedances, which requires higher capital multipliers and a “red" zone, corresponding to ten or more exceedances over a 250 day backtest period, means the model fails altogether. The test is therefore often referred to as the *traffic light* test.

With a model that could represent the current market risk levels, one could then compare them to the SIMM values and asses their adequacy. In order to get a full view of the tail risks it would be useful to obtain values at various significance levels and h-day risk horizon calibrations. The strength in the study and the findings thereof would require strict limitations set on what the objectives of the study are with clear description of the components that are the subject of scrutiny.

2.6 SUMMARY

The basics of IM and swaps is layed out in section 2.2. IM is the extra collateral that is required to be posted to cover the close-out costs and portfolio value deviations over the MPR. Since this coverage is closely linked to market risk the traditional models discussed in section 2.3 have taken the form of VaR type models. The SIMM model in contrast in section 2.4 is a SBA model that has predefined calibrations. To assess the appropriateness of the margins under SIMM the model would need to be compared to the actual risks for certain portfolios. The principles that form the methodology in chapter 3 are briefly discussed in section 2.5.

CHAPTER 3

METHODOLOGY

3.1 INTRODUCTION

The aim is to compare the IM values obtained from the SIMM and that obtained from a CCP IM calculation technique for simulated domestic SA IRS type portfolios. The CCP model is the FHS technique using generalised autoregressive conditional heteroskedasticity (GARCH) volatility scaling. The measure used in these comparisons is the ES of the simulated return distributions of various portfolios. Using various comparisons, certain questions regarding the SIMM can be answered. The comparisons allows for inspection of the SIMM IM values for different portfolio profiles and draw conclusions regarding their adequacy. The FHS ES model with GARCH scaling can be fully calibrated using only market data and makes very few distributional assumptions. There is considerable benefit in using a model that requires as little subjectivity as possible as a baseline to compare to the SIMM values.

The SIMM calculations for plain domestic IRS portfolios are very simple. There is no calibration that is required to get SIMM IM values for a given PV01 profile. The PV01 sensitivities are the only inputs to this model as all the risk weights have been pre-specified by ISDA. Therefore in order to evaluate the performance of SIMM as a risk mitigator these inputs need to be stressed. Therefore the basis of the comparisons are done for various portfolios with differing profile characteristics. These characteristics are independent of the size due to the standardisation technique that is applied throughout. Excluding liquidity and concentration features from both models allows for the assessment to be solely on the market risk coverage of the two models.

Three types of comparison are done, with each having the capability of answering its own set of related questions. First it is necessary to perform an analysis of what the IM values are under the various models for isolated cash flows expected at each of the 12 tenors. This would give an indication at which of the tenors there may be a discrepancy of the SIMM value and the CCP value. To consider the adequacy of the diversification benefits and calibrated correlations in the SIMM it would be necessary to compare the models based on standardised PV01 profiles that exhibit easily interpretable characteristics. Lastly, the SIMM and FHS models should be compared based on randomised profiles to identify the weaknesses and strengths of the SIMM. These are novel sets of experiments that aim to unravel the delta risk coverage of ISDA SIMM.

In order for the comparisons to be valid, the baseline model needs to be validated. Therefore the regulatory recommended backtests are performed on the VaR component of the ES model. This part of the procedure ensures that the model is adequately specified and that the provided comparisons can be trusted.

The rest of the chapter is organised as follows. In section 3.2 the models are compared based on their specifications and assumptions. The initial model specifications for the FHS model are also presented in this section. Section 3.3 provides the methodology for comparing the models based on profiles with isolated exposures at their tenors. Various profiles with differing characteristics and shapes are formulated for a standardised comparison of the models in section 3.4. Randomised portfolios are generated in section 3.5 and the methodology of how this comparison will be made is detailed in this section. The procedure that is employed to validate the base model is provided in section 3.6. Finally a summary of the chapter is given in section 3.7.

3.2 INITIAL MODEL SPECIFICATIONS AND COMPARISONS

It is necessary to do a preliminary evaluation of the models based on their specifications, assumptions and intention. For the comparisons to be viewed in a fair light the models themselves need to be of a comparable nature, therefore various considerations need to be taken into account. First the model assumptions and specifics must be understood before the justification is given for the various model choices when simulating from the FHS model.

3.2.1 ISDA SIMM

The SIMM is intended as a global standard way of calculating IM, simplifying the endeavour immensely and providing some much needed market consensus. When looking at a particular role of SIMM, calculating IM (delta risk) for simulated IRS type OTC portfolios, there are a number of broad simplifications that could make one suspect, despite the good intention behind it and usefulness of the application.

The risk weights used in equation 2.8 fall into three broad buckets based on the category of the underlying currency. This presents risk in the sense that some markets in one category may be over-exposed, while others may experience under-exposure, and this exposure may differ depending on the profiles of the portfolios in question. It is this risk in exposure that the following sections intend to provide some insight into.

The risk sensitivities for the SIMM are defined in section 2.4 as the present value of a basis point change. The intention of this paper is not to investigate the validity of this assumption. Therefore the CCP model should be constructed so as to have the same inputs as the SIMM model. That is, the PV01 sensitivities of the portfolio to the 12 standard tenors (2W, 1M, 3M, 6M, 1Y, 2Y, 3Y, 5Y, 10Y, 15Y, 20Y, 30Y) of the SA swap curve index. This would allow for fair comparison of IM estimates, by making the same assumption in this regard.

One of the broadest of simplifications that the SIMM introduces when calculating IRS delta are the fixed correlations. The model specifies a single correlation matrix to be used in equation 2.10, regardless of currency. This may cause the SIMM IM values to either under-compensate or over-compensate for any diversification among rates and sub-curves.

This analysis does not intend to assess the validity of the concentration risk factor (CR) that is used in the SIMM equation in 2.8. Therefore it is excluded in the calculation of the delta risk. Its exclusion is also so that its influence does not perturb the results of the analysis. No liquidity charges are added to the contender model and only the market risk is assessed.

Since these inputs are the same, the aim is to investigate how the values of IM differ for various portfolio profiles, represented by their PV01 values. These input values will therefore be of a standard nature in subsequent sections so that the focus can be on the relative IM demanded by the two models. The standardisation used will simply make the results in relative terms that allows for comparisons across the sections. Suppose that the PV01 is represented by

$$\boldsymbol{\theta}' = [\theta_{2W}, \theta_{1M}, \dots, \theta_{30Y}], \tag{3.1}$$

where each of the θ_i are the sensitivities defined in equation 2.7, for each of the tenors. Then the IM result in Rand terms for each portfolio will rather be represented as a percentage of the absolute sum of the sensitivities,

$$IM_{\%} = \frac{IM_R}{\sum_i |\theta_i|}. \tag{3.2}$$

The standardisation performed by (3.2) for the obtained results means that they do not depend on the size of the exposures in absolute terms, but rather in relative terms[1]. Therefore comparisons can be made across the various comparison methodologies. This also allows for investigation into the diversification effect of various input combinations.

Restricting the analysis to the risks of instruments that are sensitive to the SA swap index curve only, the sub-curves in the SIMM delta risk calculation (2.10) can be excluded. Define the vector of risk weights, $\boldsymbol{w}$, as the risk weights in either table 2.1 for the version 2.2 values or table 2.2 for version 2.3 and define the correlation matrix $\boldsymbol{\Omega}$ as the cross-tenor correlations found in table 2.3 or 2.4. The IM calculation of the SIMM amounts to the quick calculation

$$IM = \sqrt{\boldsymbol{s}'\boldsymbol{\Omega}\boldsymbol{s}}, \tag{3.3}$$

where $\boldsymbol{s}$ is the elementwise product of a vector of PV01 sensitivities $\boldsymbol{\theta}$ and the risk weights $\boldsymbol{w}$.

The SIMM has already been calibrated to the 10-day 99% risk level using three years of most recent data and one year of stress. To gain a better understanding of how the SIMM values change and their relative appropriateness in the current South African market both the IM results of SIMM version 2.2 and 2.3 are included in the analysis.

The CCP model employed in this analysis is an ES FHS model, that uses GARCH$(1,1)$ estimation of the volatilities of the underlying rates. GARCH is chosen specifically since it can be calibrated using market data, unlike the λ parameter in EWMA models. The inputs for the calibration is the South African swaps index curve, with the relevant tenors chosen to correspond to that of the SIMM.

[1]The subscripts % and R in (3.2) refer to the IM in percentage of PV01 exposure and the IM in nominal terms respectively.

3.2.2 Filtered Historical Simulation Model

The FHS ES model with GARCH volatility estimation is chosen because it is aligned with some of the traditional ways of calculating IM. It can also fully calibrate to market data, and no ad-hoc model choices need to be made. In addition it makes very little distributional assumptions, as it is a semi-parametric simulation technique, but maintains the complex correlation structure of the historic markets. It provides a more risk-sensitive risk estimate than the simple historic simulation technique and does not suffer from features related to sample choice like the historical method. Using such a model also allows one to obtain different values for different risk-metrics, namely α and h, to represent a holistic view of the tail risk in question.

Standard choices for the parameter values of α and h are therefore chosen for the comparisons in subsequent sections. The choices of 97.5%, 99% and 99.75% are made for α. The SIMM is calibrated at the 99% significance level and hence it makes sense to calibrate the ES estimate accordingly. The 99.75% gives a view of the possible worst-case losses that could be experienced in the most extreme events. These values therefore represent a relevant range for which a comparison with SIMM will yield informative results.

The other parameter is the h-parameter, which can be viewed as the MPR of the portfolio. If one uses a range of values, say 5, 10 and 15, one could obtain a range of the relevant risk coverage for a given α. Therefore nine different IM values are obtained for each portfolio under the FHS model. The main value is in the comparison of the 10-day 99% estimate as this is the coverage for which SIMM's parameters are calibrated. The additional estimates can give a much clearer view of the total risk coverage that SIMM is able to cover for a range of MPR scenarios and worst possible cases.

The estimation sample size for the analysis is a total of 12×2770 data points, which are the daily absolute returns in basis points of the South African Index curve at the 12 tenors starting from 6 January 2010 and ending on 14 August 2020. The curve starts at the 3M tenor and goes all the way to the 30Y tenor. The JIBAR1M rate is used as a proxy for the 1M tenor and the South African Reserve Bank Overnight borrowing Rate (SABOR) is used as a proxy for the 2W rate. This approximate ten year period should be long enough to allow for stable GARCH calibration.

The historical sample period chosen for the historical simulation is the full ten year data set described above. This is because this historic period contains several stress periods as per the regulatory IM calibration requirements for CCPs. The results should not however be too dependent on the sample period chosen, as the returns are in any case rescaled to current volatility levels. Therefore using the last three years of data would impact the results very little compared to using the full sample period. Using a longer historical period also give a richer historical return distribution to simulate from.

The chosen volatility model is a symmetric GARCH$(1,1)$ model where a zero-mean return assumption is made. The GARCH$(1,1)$ model specifies the daily conditional volatility of any of the given tenor rates to follow the process

$$\sigma^2_{t+1,i} = \omega + \alpha r^2_{t,i} + \beta\sigma^2_{t,i}, \tag{3.4}$$

for $\sigma_{t,i}$ the conditional volatility and $r_{t,i}$ the absolute return in basis points at time t for a tenor i. The parameters ω, α and β can be estimated through maximum likelihood estimation. The α parameter can be seen as the volatility's conditional response on the current market return whereas the β parameter can be seen as the persistence of the past volatility on the current volatility estimate. The ω parameter regulates the size of the LT unconditional volatility of the process.

The FHS procedure is described in detail here. The first requirement is that GARCH parameters are calibrated from the market data. These parameters are used to estimate the GARCH volatilities on each trading day in the sample. This needs to be done for each of the 12 tenor rates. Thus a standardised sample can be created by performing the division,

$$\varepsilon_{t,i} = \frac{r_{t,i}}{\sigma_{t,i}}, \tag{3.5}$$

essentially stripping the volatility away from the returns for each time, t in the historical sample period for each tenor i. This allows for the FHS algorithm, described below, to rescale the simulated returns with the current conditional volatility. Once estimation of the parameters is complete and the returns scaled to their residuals as in (3.5) the bootstrap algorithm can begin.

The bootstrap algorithm below can be applied to obtain N simulated h-day returns for the 12 tenors (2W, 1M, 3M, 6M, 1Y, 2Y, 3Y, 5Y, 10Y, 15Y, 20Y, 30Y). This is done for a standardised sample, which are the absolute daily basis point returns for each tenor after having the standardisation (3.5) performed. The volatilities ($\hat{\sigma}_0$) and the absolute returns (r_0) in basis points on the last day of the training sample (14 August 2020) are used to initialise the FHS simulations in algorithm 1.

Algorithm 1: Filtered Historical Simulation Bootstrap Algorithm

Result: N simulated h-day returns for the 12 **tenors**

for *n in N iterations* **do**

  1 Draw h random dates independently from the sample: $[t_1, \ldots, t_h]$

  2 **for** *each i in tenors* **do**

    1 Obtain $[\varepsilon_{t_1,i}, \ \ldots, \varepsilon_{t_h,i}]$ from the **standardised sample** using the indexed dates $[t_1, \ldots, t_h]$

    2 Iterate:

$$
\begin{aligned}
&\hat{\sigma}^2_{1,i} = \hat{\omega}_i + \hat{\alpha}_i r^2_{0,i} + \hat{\beta}_i \hat{\sigma}^2_{0,i} \\
&\hat{r}_{1,i} = \varepsilon_{t_1,i} \cdot \hat{\sigma}_{1,i} \\
&\hat{\sigma}^2_{2,i} = \hat{\omega}_i + \hat{\alpha}_i r^2_{1,i} + \hat{\beta}_i \hat{\sigma}^2_{1,i} \\
&\hat{r}_{2,i} = \varepsilon_{t_2,i} \cdot \hat{\sigma}_{2,i} \\
&\vdots \\
&\hat{\sigma}^2_{h,i} = \hat{\omega}_i + \hat{\alpha}_i r^2_{h-1,i} + \hat{\beta}_i \hat{\sigma}^2_{h-1,i} \\
&\hat{r}_{h,i} = \varepsilon_{t_h,i} \cdot \hat{\sigma}_{h,i}
\end{aligned}
$$

    3 Obtain h-day estimate $\hat{R}_{i,n} = \hat{r}_{1,i} + \cdots + \hat{r}_{h,i}$

  end

end

Return the matrix $\boldsymbol{R}$ ($12 \times N$) of N simulated h-day returns for each tenor

The result is N simulated returns for each of the tenors. To obtain the expected shortfall estimate at a given α level using a set of simulated h-day distributions ($\boldsymbol{R}$) for a given PV01 profile ($\boldsymbol{\theta}$) first obtain the product

$$
\boldsymbol{d} = \boldsymbol{\theta}' \boldsymbol{R}. \tag{3.6}
$$

The vector $\boldsymbol{d}$ contains N simulated returns for the portfolio. From this distribution the VaR estimate needs to be obtained at the α significance level as in equation 2.1. For N = 1000, the empirical 99% VaR estimate would be the 10th largest loss of the simulated returns in $\boldsymbol{d}$. The related empirical ES estimate, which is used as an IM estimate in these analysis, is simply the average of the largest losses above the VaR. Thus formally,

$$
ES_R = -\frac{1}{N(1-\alpha)} \sum_{i \leq N(1-\alpha)} d_{(i)}, \tag{3.7}
$$

where $(d_{(1)}, d_{(2)}, \ldots, d_{(N)})$ denotes the ordered portfolio returns of $\boldsymbol{d}$ from smallest to largest[2].

The FHS bootstrap technique allows for the number of data points at each tenor to exceed the original sample of historic daily returns, whereas with a historic simulation model the sample size would decrease when using non-overlapping daily returns for an h-day VaR calculation. The FHS technique by nature will require a different simulation for each h-day estimate. These simulations will generate a distribution from which the alpha quantiles can be taken.

It would be better to simulate a very large distribution of 10 000 h-day returns for each tenor rate than to generate only 1000 observations for each comparison in subsequent analysis. It is too computationally expensive to run large simulations for each specified h, and for each comparison. Therefore for the three h parameters (5, 10, 15) 10 000 simulated returns are created from which the ES estimates can be drawn. This means that all the analysis is based on the same set of simulations.

To avoid procyclicality issues related to these kinds of models CCPs use a volatility floor technique to stabilise the volatilities toward their LT estimates. This requires either ad-hoc choices for the slack of the volatility stabilisation, or optimisation for the parameter through various bootstrap optimisation techniques which is beyond the scope of this analysis. The use of the current volatility estimates will give a more point in time relevant understanding of the risks involved.

There are some departures from reality that is introduced with such a model. For one it assumes that the PV01 sensitivities remain constant over the h-day period. This is of course not the reality, as the PV01 sensitivities would need to change at each node of the FHS simulation. PV01 sensitivities are used in the FHS model in order to easily compare with the SIMM and evaluate the risks, which imposes them as the necessary risk factors. Therefore this model assumes fixed PV01 values, which is applied to an empirically simulated h-day return as an approximation for the portfolios PV movements over the period.

To see the relevant risks of the risk weights and correlations of SIMM when employed in the South African domestic swap market, one needs to understand the risks of the risk weights at the isolated tenors before investigating how the correlations influence the results. This is what the next section aims to lay out, a basic understanding of the potential shortcomings of the SIMM risk weights.

[2]The subscript, R, in equation 3.7 denotes that the ES result is in Rand terms and the standardisation (3.2) still needs to be applied to obtain the IM as a percentage of absolute PV01 exposure.

3.3 COMPARISON OF ISOLATED TENOR EXPOSURES

The methodology for assessing the risk weights of the SIMM is presented in this section. A way to compare the relative IM values under SIMM (version 2.2 and 2.3) versus the quantile risk estimates for the risk parameters in section 3.2 is detailed. This section follows the lines of Barnes (2016), but performs the analysis specifically for the SA market. This methodology allows for fair evaluation of the adequacy of the SIMM for isolated exposures at maturities that correspond to the vertices in the IM models.

If the results of the FHS model exceeds the SIMM at the necessary risk levels then it would indicate that the SIMM model may have some shortcomings due to its broad calibration. The SIMM model is also symmetric and gives the same IM value regardless of the sign of the exposure. The FHS model by nature offers a distribution with two sided tails. One's exposure to each of these tails depends on whether they are paying fixed or paying floating, thus producing different IM estimates depending on the signs of the PV01 exposures. Creating profiles for both long side and short side exposures allows for an assessment of the SIMM risk weights at each of the extreme quantiles.

A note on terminology is in order as the following discussions use the terms REC, to refer to the long side, and PAY to refer to the short side. Here, the term REC refers to the party in the swap that is receiving the floating rate. Therefore a basis point increase in the sensitivity results in a positive increase in the PV of their portfolio. The PAY side refers to the party paying the floating rate, hence a basis point increase results in an increase of outgoing liabilities producing a loss. The terms long and short will often also refer to the REC or PAY side of the trade respectively.

As explained in section 3.2 three simulations (for $h = 5$, 10 and 15) are run to generate 10 000 simulated h-day returns for all the analysis. Applying a PV01 profile with only a unit PV01 exposure to one of the tenors and no exposure to the others allows one to generate a distribution of returns for any single risk factor. A positive position indicates an exposure to the risk of the relevant rate decreasing and a negative position the risk of the relevant rate increasing.

With the same inputs fed into the SIMM and CCP models, comparisons can be made using these portfolios for each risk metric combination of α and h. For these comparisons to be comparable across tenors and for the results to be independent of the initial value chosen for the PV01 exposure, the value obtained for the IM is expressed as a percentage of PV01 exposure as in equation 3.2. The choice of using only a single unit PV01 exposure inputs results in the output already given in percentage form. Such a standardisation is much more informative than simply looking at absolute values returned by the models, since the results are generalisable. Similar standardisation techniques are applied in subsequent comparisons so that results can even be compared across comparison methodologies.

It is worth looking at the risk weights for the high-volatility currencies in the current SIMM version 2.2 (table 2.1) and the risk weights for the newer version 2.3 (table 2.2). This could also show which margins of the latest available SIMM versions are appropriate for isolated exposures. In addition to using these two versions for the high-volatility currencies, the currency bucket appropriate for South Africa, the regular currencies risk weights of tables 2.1 and 2.4 are also included in the analysis. The SIMM results for the high-volatility currencies are referred to as "SIMM SA", and the IM results from the regular currencies is termed "SIMM UK"[3].

The output of this analysis can be summarised in table form and presented graphically for ease of interpretation. One can additionally compare the average results of the FHS model and the SIMM models since the PV01 standardisation of (3.2) leads to maturity agnostic IM measures in this case. For a given risk metric of α and h, the results for each of the tenors including the average result, can be compared. At the tenors that produce large deviance's one can investigate the source of the result, at least from the perspective of the CCP model.

Since a distribution is generated for each of the tenors in this methodology a histogram plot of the simulated distributions can be generated and compared to the empirical distribution of that rate. This acts as a visual validation of the FHS model, and may help justify the results obtained.

To gain further insight into the appropriateness of the SIMM models, one can look at the estimated volatilities at each of the tenor rates. Volatility estimates worth comparing include the equally weighted sample standard deviation of the individual rates, as well as the GARCH volatilities that are estimated. From the GARCH parameters estimated it is possible to generate LT unconditional volatility estimates[4]. These estimates can be compared with the risk weights in SIMM and

[3]Note that the data used are the same, the only difference is the risk weights used; the terminology is there for simplification.

[4]Provided that the parameter estimates for α and β satisfy $\alpha + \beta < 1$.

the relative size of these could help explain the differences in the IM values obtained during the comparison.

The comparison of isolated tenor exposures methodology gives insight into the risk weights of the SIMM models. This shows where the weaknesses and strengths of the SIMM calibration lie with regard to these fixed parameters. It does not, however, take into account the correlation matrix for interest rate portfolios presented by SIMM, nor does it account for concentration risk. This allows for a focused look on the risk weights, whereas the standardised comparison of portfolio profiles section aims to investigate the influence of these correlations as well as highlighting some additional advantages and potential shortcomings of the SIMM models.

3.4 STANDARDISED COMPARISON OF PORTFOLIO PROFILES

The term standardised comparison of portfolio profiles refers to using fixed inputs of the portfolio profiles, represented by their PV01 vectors ($\boldsymbol{\theta}$) to give insight into how the two models perform in terms of their calibration to volatilities and correlations. This novel method uses standard[5] shapes as well as their inverses for long and short portfolios are used to produce PV01 inputs for the SIMM and FHS models. Anomalies in the IM results could help asses where the risks lie for various forms of the input combinations.

This section aims to describe a novel methodology for comparing the results from the models in a standardised way to gain insights into the influence of the shapes of the inputs on the IM estimates in an easily interpretable manner. The aim is to make the results so that they can be compared to the results obtained in the previous section. The previous results will also help inform the insights gained from the analysis described here with an additional look at the diversification effects of the models. Note that the profiles in this section will have names that have arbitrary meaning in all aspects other than referring to the relative weights used in the input vector, $\boldsymbol{\theta}$. This makes analysis of the influence of various profile shapes on the relative results of the SIMM in comparison to the FHS much clearer.

The shapes chosen for the inputs are here called flat, ST vs LT, linear, sine, cosine, exponential and

[5]The word "standard" or "standardised" is terminology that is introduced to refer to the shapes of the created profiles with respect to their PV01 sensitivities. This allows for attention to be focused on the shape of profiles and enables the aims of this section to be clearly presented. It does not refer to standard realistic portfolios in any way and is not to be confused with terminology that may be used in other literature.

alternating. These PV01 vectors, given in tables 3.1 to 3.7, are created to have these standard shapes, where some are visualised in figures 3.2 to 3.6. These are given for profiles with long only (LO) exposures, meaning only positive PV01 values, short only (SO) exposures, meaning only negative sensitivities, and long-short (LS) exposures, having both positive and negative PV01 inputs. Results are also produced for other shapes that provide additional insight, such as initially increasing and decreasing variations. An alternating portfolio profile that has alternating positive and negative values, and flat LT versus ST profiles can also provide insight into some of the correlation risks and diversification benefits of the SIMM. These profiles are not meant to represent real portfolios, but rather chosen for their capability of revealing any risks with regard to calibrated risk weights and correlations.

The results obtained here will have the standardisation (3.2) applied. Note that this will not change the relative results of the SIMM with the FHS model in each individual comparison, as the standardisation denominator is the same for both models. However, this does make it possible for the IM results to be compared across profile types.

The first and most important comparison to make is the flat profile comparisons. Although not graphically shown here, since the shape is very simple, the inputs can be found in table 3.1. Only the LO and SO variations are assessed here as the intention is to give equal weight to all the risk weights in SIMM. The SIMM is by nature symmetric, but the FHS model is far from that. Therefore the results of the FHS model will rarely be the same for the LO and SO sides despite their same sizes in exposure. The absolute size of the inputs do not matter as the CR element of SIMM is ignored and the IM results are standardised in any case.

Table 3.1: Flat profiles used in the standardised comparison analysis.

Type	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	1	1	1	1	1	1	1	1	1	1	1	1
SO	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

To supplement the findings of the analysis employed in the previous section it is necessary to look at the profiles referred to as the *ST vs LT* (short-term versus long-term) comparison. From the figures in 3.1 and table 3.2 these profiles give weight to either the ST tenors or the LT tenors. This is alternated for LO exposures and SO exposures. The LS profile is also fed into the two models to see how the models handle the correlations and risk of the short versus the long end of the curve.

Table 3.2: ST versus LT profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	ST	1	1	1	1	1	1	0	0	0	0	0	0
	LT	0	0	0	0	0	0	1	1	1	1	1	1
SO	ST	-1	-1	-1	-1	-1	-1	0	0	0	0	0	0
	LT	0	0	0	0	0	0	-1	-1	-1	-1	-1	-1
LS	ST	0.5	0.5	0.5	0.5	0.5	0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
	LT	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.5	0.5	0.5	0.5	0.5	0.5

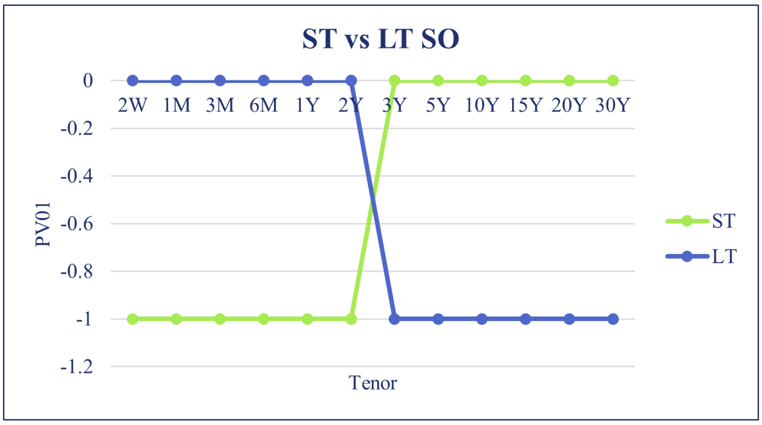
The linear profiles presented in table 3.3 and plotted in figures 3.2 and 3.3 are used to investigate the behaviours of the SIMM compared to the FHS model for profiles with large sensitivities at the LT or ST ends of the curve. The LO increasing profile will highlight any risks in the loss coverage over a given MPR of the SIMM model for portfolios with a larger weightings on the LT tenors. The LO decreasing profile highlights the same risks but for portfolios with cash flows of shorter maturities. Since the FHS model is not symmetric it is also worth looking at the exposures with negative values as well. The linear increasing SO profile is essentially the negated values of the linear increasing LO profile, but the results from this standard input is more comparable with the results from linear decreasing LO. This is because they both compare weightings concentrated on the short end of the input spectrum, but essentially looking at the opposite end of the tail risk[6]. The same analysis can be achieved for the LT sensitivities end by looking at the linear increasing LO and the linear decreasing SO profiles.

There is additional benefit at looking at a the results of portfolios with long and short exposures, i.e. having both positive and negative values as inputs into the models. This can show how the SIMM model compares to the FHS model in terms of its ability to account for some of the diversification benefits. The linear increasing LS profile could show how much diversification is achieved by the models for portfolios with negative ST exposures and long LT exposures. The linear decreasing LS profile would show the diversification effects for a portfolio with positive ST sensitivities and negative LT sensitivities.

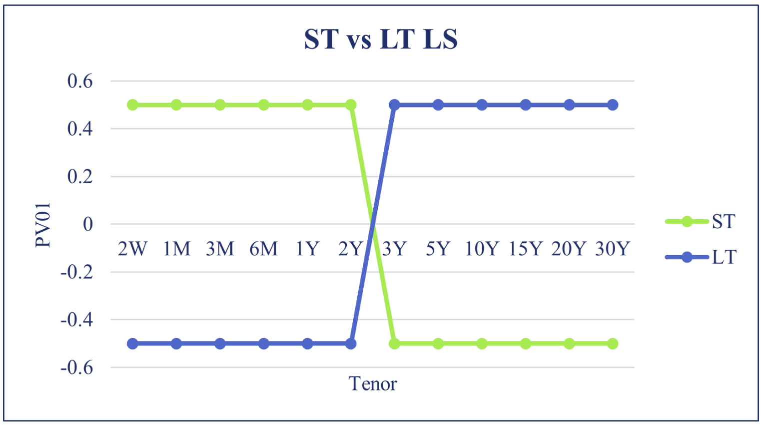
Using sine and cosine like forms for the tenor input variables, one can obtain results that show

[6]Note that the SIMM models are symmetric and should therefore produce the same results for the linear decreasing LO and linear increasing SO.

(a) ST versus LT LO profiles.



(b) ST versus LT SO profiles.



(c) ST versus LT LS profiles.

Figure 3.1: Graphs representing the LT versus ST profiles used in the standardised comparison analysis.

Table 3.3: Linear profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	Increasing	0.00	0.09	0.18	0.27	0.36	0.45	0.55	0.64	0.73	0.82	0.91	1.00
	Decreasing	1.00	0.91	0.82	0.73	0.64	0.55	0.45	0.36	0.27	0.18	0.09	0.00
SO	Increasing	-1.00	-0.91	-0.82	-0.73	-0.64	-0.55	-0.45	-0.36	-0.27	-0.18	-0.09	0.00
	Decreasing	0.00	-0.09	-0.18	-0.27	-0.36	-0.45	-0.55	-0.64	-0.73	-0.82	-0.91	-1.00
LS	Increasing	-0.50	-0.41	-0.32	-0.23	-0.14	-0.05	0.05	0.14	0.23	0.32	0.41	0.50
	Decreasing	0.50	0.41	0.32	0.23	0.14	0.05	-0.05	-0.14	-0.23	-0.32	-0.41	-0.50

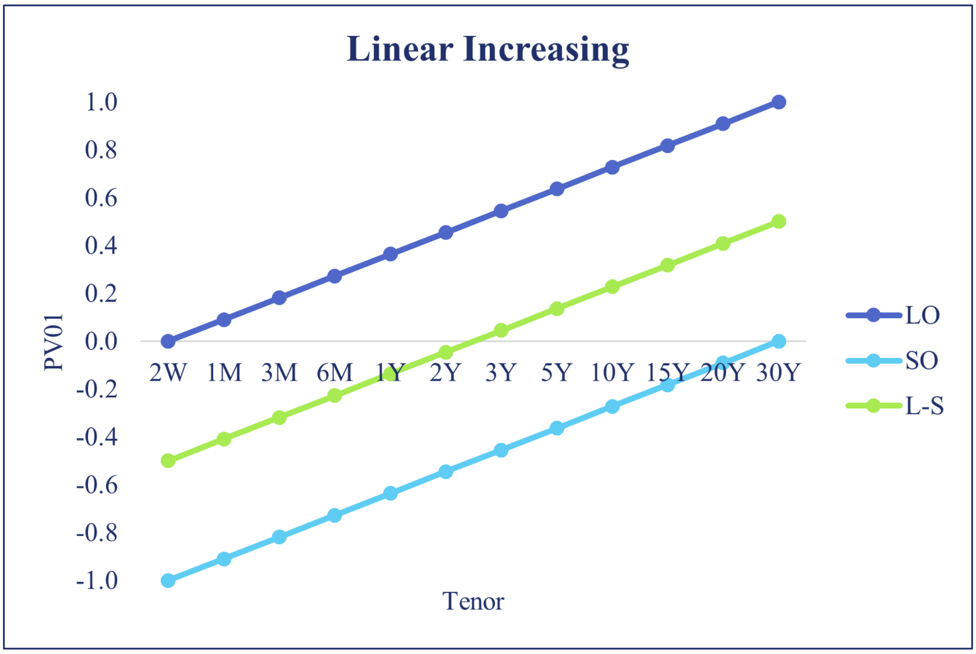


Figure 3.2: Graph illustrating the shape of the linear increasing profiles for the LO, SO and LS variations.

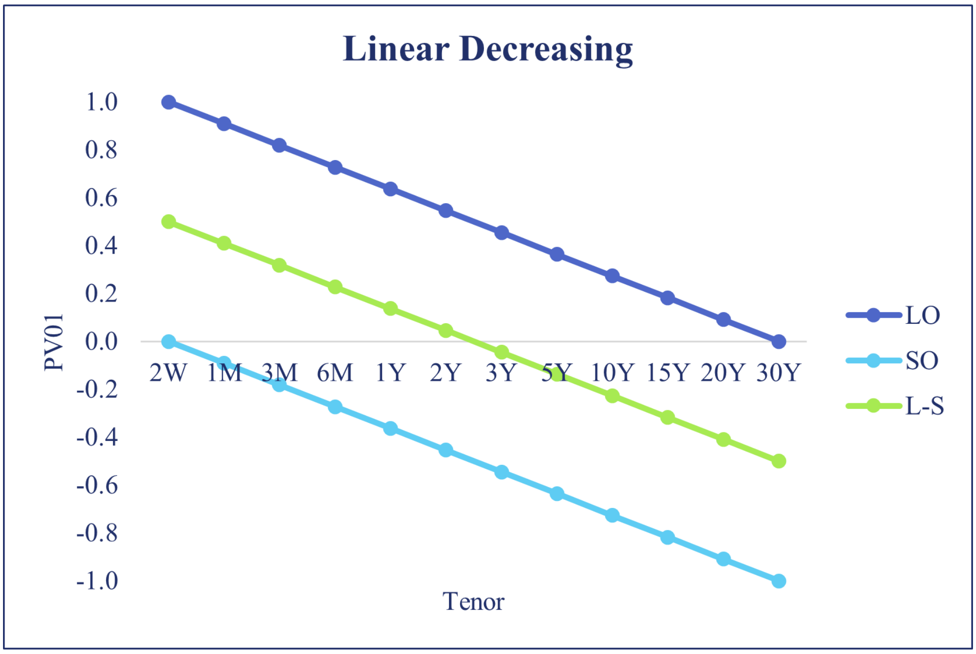


Figure 3.3: Graph illustrating the shape of the linear decreasing profiles for the LO, SO and LS variations.

additional information of the influences of the SIMM inputs on the IM values. The sine PV01 values are given in table 3.4 and the cosine profiles are given in table 3.5. Here the terms increasing and decreasing refer to the initial slopes of the profiles, rather than their general direction, since these functions oscillate. One can see from figure 3.4, which displays the LS profiles for the sine and cosine profiles, how these profiles emphasise their weightings at different tenors. This is what allows for a more in depth understanding of the risk coverage provided by the SIMM.

The sine increasing LS, in figure 3.4, has a maximal sensitivity of 0.99 at the 6M tenor and a minimal sensitivity of -0.99 at the 10Y tenor. Therefore a good profile to use when inspecting the diversification risks of the mid-ST tenors versus the mid-LT tenors. The LO and SO versions of this form include only positive and negative values respectively. Each of these variations provide additional insights when comparing the results. Similarly the cosine increasing LS, in figure 3.4, has maximal weights at the 2Y and 3Y tenors of 0.96 and minimal weights of -1 at the 2W and 30Y tenors. The LS, LO and SO variations of the cosine form will give similar beneficial insights as the sine forms.

The exponential profiles given in figure 3.5 and table 3.6 give yet another form for the inputs in the

Table 3.4: Sine profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	Increasing	1.00	1.54	1.91	1.99	1.76	1.28	0.72	0.24	0.01	0.09	0.46	1.00
	Decreasing	1.00	0.46	0.09	0.01	0.24	0.72	1.28	1.76	1.99	1.91	1.54	1.00
SO	Increasing	-1.00	-0.46	-0.09	-0.01	-0.24	-0.72	-1.28	-1.76	-1.99	-1.91	-1.54	-1.00
	Decreasing	-1.00	-1.54	-1.91	-1.99	-1.76	-1.28	-0.72	-0.24	-0.01	-0.09	-0.46	-1.00
LS	Increasing	0.00	0.54	0.91	0.99	0.76	0.28	-0.28	-0.76	-0.99	-0.91	-0.54	0.00
	Decreasing	0.00	-0.54	-0.91	-0.99	-0.76	-0.28	0.28	0.76	0.99	0.91	0.54	0.00

Table 3.5: Cosine profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	Decreasing	2.00	1.84	1.42	0.86	0.35	0.04	0.04	0.35	0.86	1.42	1.84	2.00
	Increasing	0.00	0.16	0.58	1.14	1.65	1.96	1.96	1.65	1.14	0.58	0.16	0.00
SO	Decreasing	0.00	-0.16	-0.58	-1.14	-1.65	-1.96	-1.96	-1.65	-1.14	-0.58	-0.16	0.00
	Increasing	-2.00	-1.84	-1.42	-0.86	-0.35	-0.04	-0.04	-0.35	-0.86	-1.42	-1.84	-2.00
LS	Decreasing	1.00	0.84	0.42	-0.14	-0.65	-0.96	-0.96	-0.65	-0.14	0.42	0.84	1.00
	Increasing	-1.00	-0.84	-0.42	0.14	0.65	0.96	0.96	0.65	0.14	-0.42	-0.84	-1.00

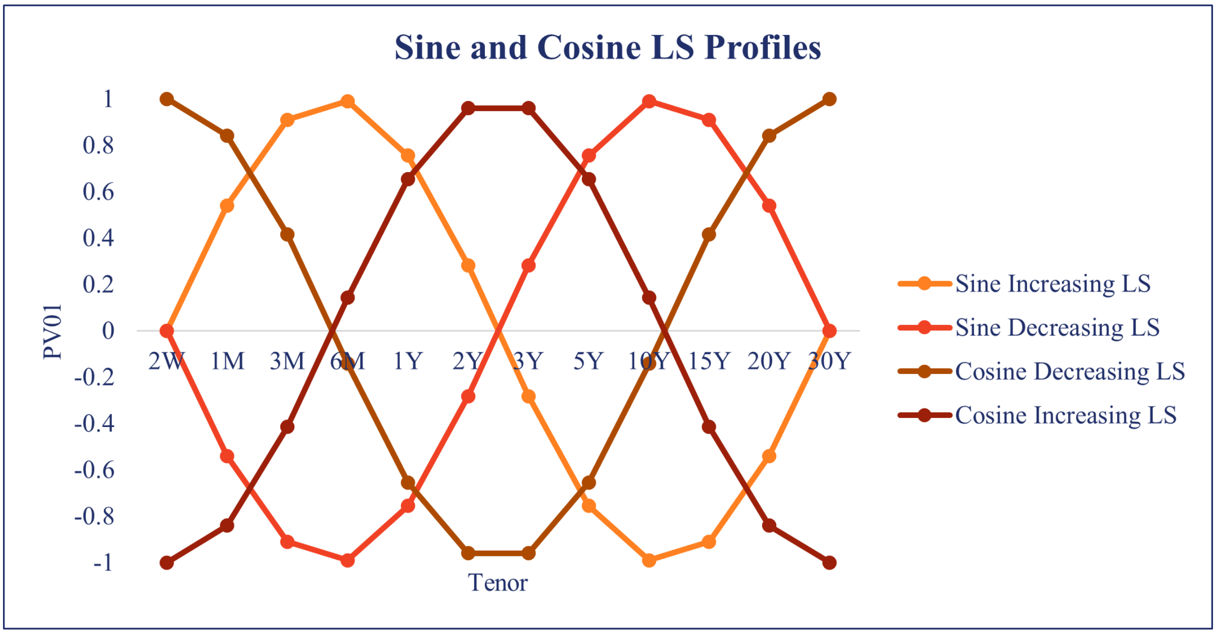


Figure 3.4: Graph illustrating the shape of the sine and cosine profiles for LS variations only. The LO and SO variations would have shapes that are shifted up or down by one unit at each tenor respectively.

model. The exponential inputs' results should be closely compared with the results obtained from the linear inputs. Although the exponential gives more relative weight to the ST and LT tenors than the linear inputs. This offers additional insight into the risks of skewed portfolios.

Table 3.6: Exponential profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	Increasing	0.01	0.02	0.02	0.04	0.05	0.08	0.12	0.19	0.28	0.43	0.66	1.00
	Decreasing	1.00	0.66	0.43	0.28	0.19	0.12	0.08	0.05	0.04	0.02	0.02	0.01
SO	Increasing	-1.00	-0.66	-0.43	-0.28	-0.19	-0.12	-0.08	-0.05	-0.04	-0.02	-0.02	-0.01
	Decreasing	-0.01	-0.02	-0.02	-0.04	-0.05	-0.08	-0.12	-0.19	-0.28	-0.43	-0.66	-1.00

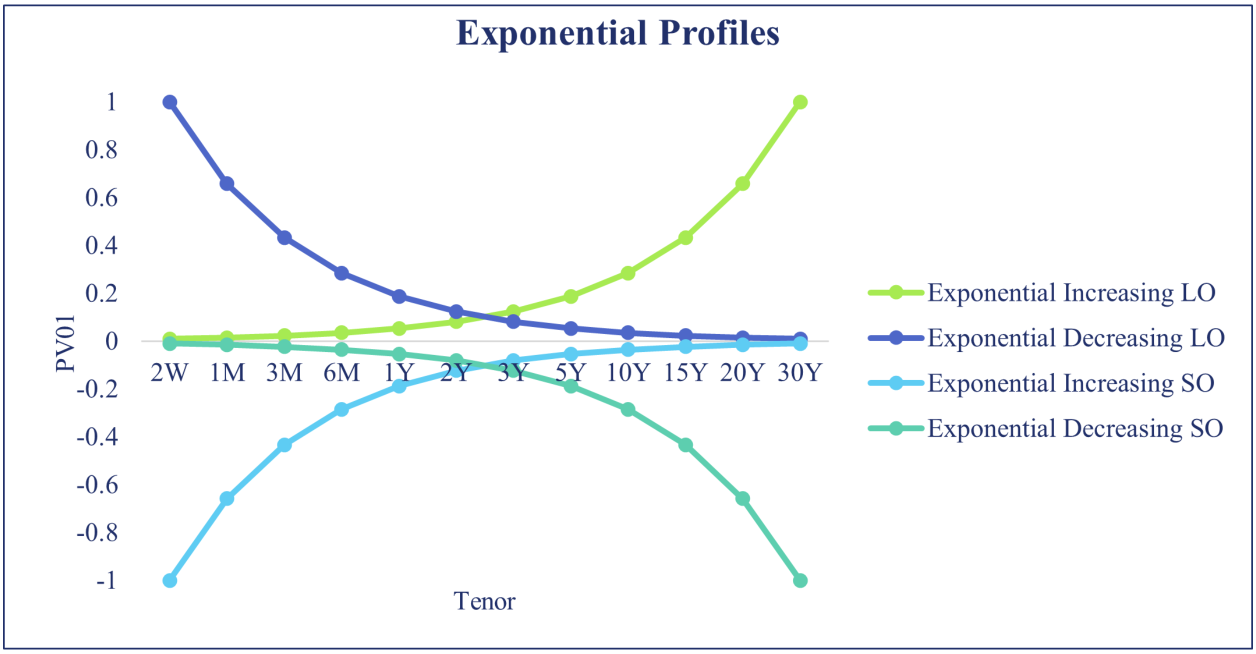
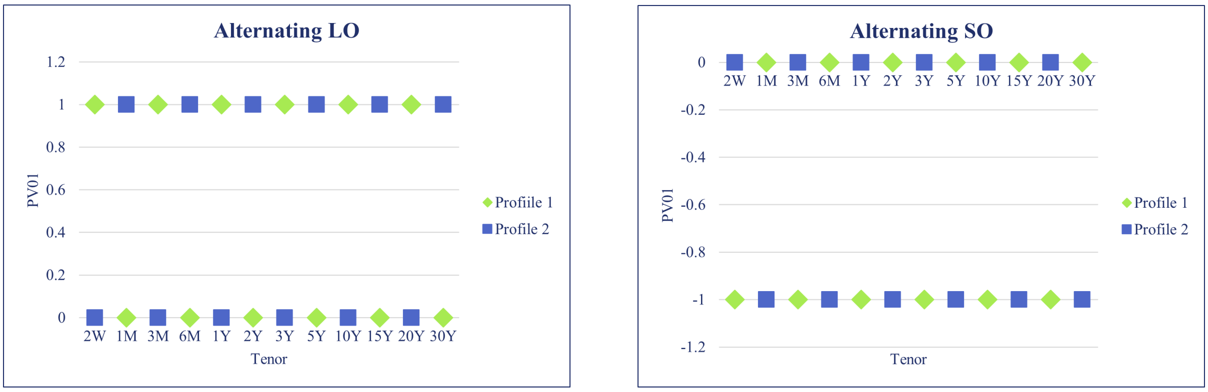


Figure 3.5: Graph illustrating the shape of the increasing and decreasing exponential profiles for the LO and SO variations.

The alternating comparisons will help uncover if any combinations of inputs are particularly ill-specified. Again the use of LO, SO and LS variations will give insight into the tail risks and to what extent the diversification is accounted for in the SIMM model. These comparisons can be viewed alongside one another and alongside earlier comparisons. This allows for a deeper understanding of the correlation risks.

In order to unravel the potential misspecification of the SIMM correlations it would be helpful to view the correlations of the risk factors in a similar framework as the SIMM. That means estimating the



(a) Alternating LO profile.

(b) Alternating SO profile.

Figure 3.6: Graphs illustrating the shapes of the alternating profiles.

Table 3.7: Alternating profiles used in the standardised comparison analysis.

Type		2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	Profile 1	1	0	1	0	1	0	1	0	1	0	1	0
	Profile 2	0	1	0	1	0	1	0	1	0	1	0	1
SO	Profile 1	-1	0	-1	0	-1	0	-1	0	-1	0	-1	0
	Profile 2	0	-1	0	-1	0	-1	0	-1	0	-1	0	-1
LS	Profile 1	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5
	Profile 2	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5	-0.5	0.5

correlations of the risk factors and comparing them with the calibrated SIMM weights. Assuming a linear correlation structure may be too naive in the first place, hence the choice for using a non-parametric model for the comparison, which makes no distributional assumption regarding the correlations[7].

This section gives a way to see where, if any, weaknesses in the SIMM model lie, and aims to understand and explain the source of these weaknesses. While the methodology is aimed at being understandable and informative, it fails to do an exhaustive stress test of the inputs. The next section aims at describing a procedure for analysing the greatest strengths and weaknesses of the SIMM models.

3.5 RANDOMISED PORTFOLIO COMPARISONS

The analysis described in this section involves stressing the inputs using randomly generated input values. The inputs that result in the largest SIMM and smallest SIMM IM estimates in comparison to the FHS model will then need investigation. This section describes these novel procedures and what can be gained from this methodology.

This stressed scenario testing does not aim to use extreme values for the analysis, but rather randomly generated input values that are relatively different from one another. This is to further assess the diversification and correlation risks that could be present in the SIMM model. Therefore normally distributed PV01 values are generated as apposed to uniform values. Any combinations or profile shapes not captured in the prior analysis will be evident here. From this it is possible to see for which profiles the SIMM behaves differently to the FHS model. These profiles can be compared with each other and to the profiles used in previous analysis to form a holistic understanding of the risks inherent to using SIMM for capturing delta risk.

To perform the comparisons independent random normal $N(0, 1)$ variables are generated for each of the tenors. 1000 such portfolios are created for each type of comparison. A comparison is made for LO, SO and LS profiles like in the previous section. The LO profiles are the absolute values of independent identically distributed $N(0, 1)$ random simulations for each tenor and the SO portfolios are the negative of the absolute value of its own i.i.d. $N(0, 1)$ simulations. This results in

[7]The model does assume that the historical processes are a precursor for future returns.

random portfolios of only positive and negative values respectively. The LS profiles here represent completely random portfolio distributions and will have the added advantage of showing for which types of portfolios the diversification benefit of the SIMM model is too generous. A random sample of each of these is presented in table 3.8 and figure 3.7.

Table 3.8: Sample random profiles for each of the types of randomised comparisons performed.

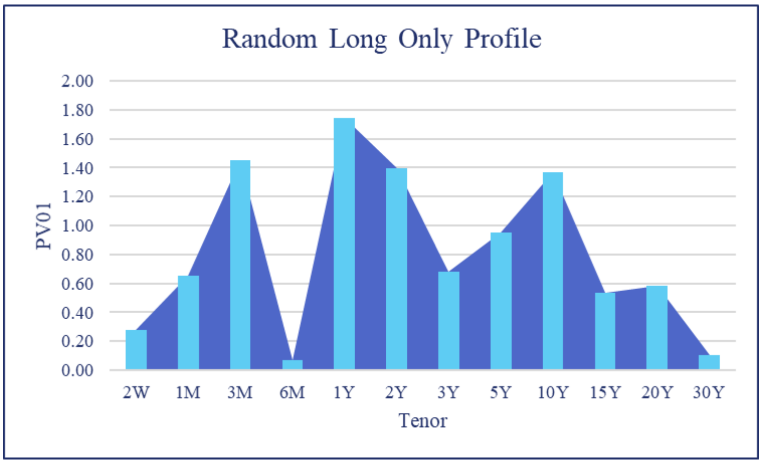
	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LO	0.28	0.65	1.45	0.07	1.74	1.40	0.68	0.95	1.37	0.54	0.59	0.10
SO	-1.09	-0.86	-0.53	-0.11	-1.09	-0.42	-0.26	-0.26	-0.89	-0.59	-0.07	-0.74
LS	-1.08	-0.94	-0.43	-0.32	-1.90	-0.07	0.07	-0.53	0.31	-0.50	0.47	0.18

The IM results of the models are again standardised using (3.2), thereby making the results of the each of the random simulations comparable. This again allows for averages to be taken and it allows the relative comparisons, explained below, to take place.

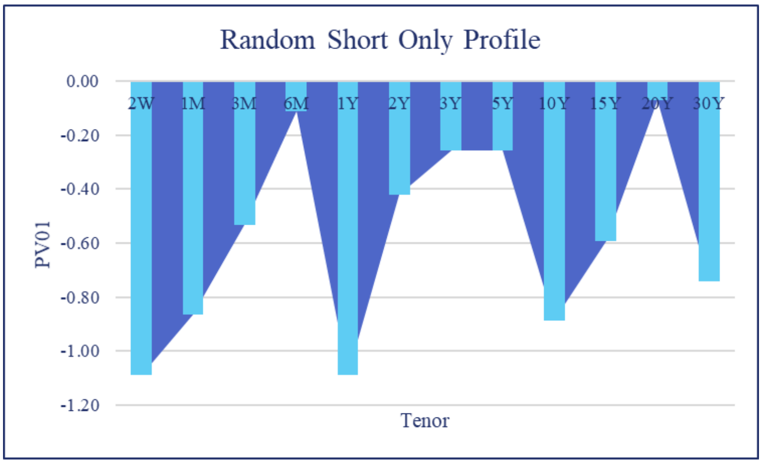
The profiles worth investigating are those that produce the largest differences between the SIMM and CCP models. This would indicate whether there are some portfolio forms that the SIMM model is less capable of covering due to its broad calibration. It would also be worth looking at the portfolios that generate the largest and smallest SIMM values. Likewise, the portfolio that generates the largest IM estimated for the FHS model would be worth including in the comparison. This can be very informative of risks especially if there are major differences in the shapes of these portfolios.

The profiles of interest for the LO and SO analysis should be compared. This would also give an understanding of the two sided tail quantile risk of the distribution of a portfolio. If differences in the shapes for the LO and SO profiles exist for any of the noteworthy profiles, then it would indicate that a symmetric specification of the tail risks may also be too naive.

The analysis described here and in the previous sections help uncover where the SIMM model may leave exposures. The procedure for the analysis is conducted in this way to sequentially build an understanding of the model risks that may present themselves. In all of these comparisons the SIMM is compared to the FHS model. To impart confidence into the FHS model that is used throughout for the comparisons, it would be beneficial to validate the model. This would essentially substantiate the results obtained in the analysis.



(a) Random LO profile.



(b) Random SO profile.

(c) Random LS profile.

Figure 3.7: Graphs illustrating a sample of the random profiles for each of the LO, SO and LS variations.

3.6 MODEL VALIDATION

Here a methodology for assessing the validity of the CCP model used in the subsequent comparisons is presented. Applying regulatory backtesting standards to the FHS model will fortify confidence in the analysis conducted prior. The technical specifications and the reasons for the validation choices are given in this section.

The regulatory backtests recommend performing an out of sample backtest of the 1-day VaR model at the 99% confidence level over a period of at least one year. The procedure here will follow the similar recommendations but explicitly testing the models capability of forecasting ahead. The 5-day VaR model will be tested at the 99% alpha level against out of sample overlapping 5-day empirical returns for the last 250 days in the sample used in the analysis, using a standard flat positive profile (table 3.1). The choice of profile is arbitrary, but can be viewed as giving each of the tenors an even weighting in the validation procedure.

Although the analysis uses the ES estimates produced, the validation methodology is based on the VaR estimates. This is in part because it is easier to test the VaR values than the ES values due to sample size constraints. If the VaR model passes the backtest, it does not necessarily imply that the ES model would pass the backtest, but one can at least be confident that the tails of the distribution are well specified to a certain degree.

The number of test observations becomes larger as h increases, unless one uses overlapping days to create h-day returns. It is also commonplace to use overlapping samples in practice, however it naturally introduces auto-correlation into the test samples. Therefore fixed rolling sample size of 2200 daily absolute basis point returns are used to calibrate the GARCH parameters for the model. This is also the sample from which FHS bootstraps are drawn at each node of the backtest, to produce 99% VaR estimate for the specified portfolio at each of the 250 days.

The procedure is therefore as follows. Estimate the GARCH parameters over the fixed sample. Generate a 5-day distribution of the returns for the chosen portfolio. Estimate the 99% VaR estimate from this sample and compute the 5-day empirical return over the subsequent five days after the estimation sample has ended. Produce the indicator as in (2.14) if the empirical loss exceeds the VaR estimate. Repeating this for $n = 250$ days allows the hypothesis (2.17) to be formulated. Thus the model is rejected if the number of exceedance is 6 or less, falling outside the confidence bounds in (2.19)

The procedure to perform this backtest is quite resource intensive as the FHS simulations need to be recreated at each of the 250 iterations. Therefore only 1000 simulations are run at each iteration, rather than the 10000 used in the analysis. If one were to use more simulations then the VaR model would be more accurate than the one being tested in this section.

The reason a 5-day backtest is run as opposed to a 1-day backtest, is specifically to show the strengths of the FHS model in producing h-day ahead distributions. The reason a 5-day backtest is run as opposed to a 10-day or 15-day, is due to the overlapping h-day samples distorting the backtest results. The 5-day overlapping empirical samples will still have autocorrelation introduced, but certainly not as pronounced as the 10- or 15-day cases. This serves as a reasonable trade-off for assessing the validity of the results.

This section does not intend to distract from the prior analysis conducted, but rather to act as a reassurance for the results obtained. Therefore only one type of backtest is run for one type of portfolio. The fact that the VaR and ES models are consistent in this framework, the backtest serves as an assurance for the validity of the analysis made.

3.7 SUMMARY

A methodology and framework for assessing delta risk in the ISDA SIMM is presented in this chapter. The results from the SIMM are compared against the results of an FHS ES model that uses GARCH$(1, 1)$ volatility scaling. The assumptions for both models are initially discussed in section 3.2, where the details regarding the data sample and algorithms are presented. The framework follows three experiments, where each assessment builds on the preceding one. First a testing methodology to asses the SIMM risk weights in isolation is presented in section 3.3, then by using standard shapes for the PV01 input profiles (section 3.4), deeper analysis can be conducted that incorporates the correlations of the SIMM. The final experiment, in section 3.5, uses randomly simulated inputs to stress the input space of the SIMM model. Throughout these analysis the liquidity factors are excluded and the results are standardised into percentage terms, so that the results are more generalisable and independent of total absolute size.

CHAPTER 4

RESULTS

4.1 INTRODUCTION

The results for the three analysis methodologies and validation procedure, described in chapter 3, are presented here. These results are presented in a scheme whereby prior analysis informs the understanding of subsequent analysis. The results of the isolated tenor comparisons will inform much of the differences in the values obtained throughout. This helps form the necessary understanding when evaluating the findings for the standardised comparison. The standard comparisons give a preliminary look into the differences between the model results which allows for a thorough look at the various tail estimation risks in the random comparison analysis. The test results of the validation procedure reaffirm the findings of this chapter.

The first experiment that is analysed in section 4.2 is that of the isolated tenor exposures. This is a crucial comparison that compares the FHS model at various risk calibrations with the SIMM model, and is the first inspection of the calibrated risk weights for high-volatility currencies in the domestic SA OTC IRS market. This section presents the SIMM risk weights for high-volatility currencies for version 2.2 and version 2.3. The risk weights for regular currencies are also included for a brief look into their appropriateness. To get a better understanding of the individual distributions that lead to these results certain rates' volatilities and distributions are analysed.

Section 4.2 contains the results and discussion from conducting the analysis described in section 3.4 for various standardised portfolio PV01 profiles. This is the first time the calibrated correlations of SIMM play a role in the IM values, which is necessarily different to the correlations within the simulated distributions. The standardised shapes allow for an understanding of how the risk weights and correlations work with each other for different combinations. These findings equip one for the next analysis given in section 4.4.

The randomised comparisons have the potential to confirm the findings of previous sections. Here some of the same shapes and results can be seen that are evident in sections 4.2 and 4.3. Novel results are also found, that present themselves due to the randomised nature of the comparison methodology, described in section 3.5.

Lastly a validation is conducted on the 5-day 99% VaR model that is consistent with the ES model that produces the results analysed in the sections introduced above. This brief section (4.5) follows the specifications laid out in section 3.6 and aims to solidify the comparisons and findings made in this chapter.

4.2 RESULTS OF ISOLATED TENOR EXPOSURE COMPARISONS

This section aims to analyse the risk weights of the SIMM by comparing them to an FHS ES model. The margin appropriateness for isolated exposures at each of the tenors can be uncovered. The results are discussed for the analysis conducted using the methodology presented in section 3.3. This section gives the IM as a percentage of absolute PV01 exposure for portfolios with isolated exposures at each tenor, for the long side (REC) and short sides (PAY) of the swap trade. The FHS ES results are presented and discussed for various risk calibrations of the h and α parameter, with the primary focus being on the 10-day 99% calibration.

The entirety of the results from the analysis in this section are given in tables 4.1 to 4.3. The IM values of SIMM as well as the h-day α ES estimates from the FHS model are given for isolated exposures at each tenor expressed as a percentage of PV01. Table 4.1 shows the results from using exposures with unit positive PV01 values at each tenor, whereas table 4.2 gives the results for unit negative PV01 inputs. The average of the values in these two tables are given in table 4.3. The FHS values in table 4.1 represents the left tails of the simulated distributions and are referred to as "*REC*", since under this framework it represent the exposure for the party of the swap receiving floating. Those values in table 4.2 represent swap exposures to those paying floating, hence they are called "*PAY*" for short, and they represent the quantile risk estimates of the right tails of the simulated distributions.

Note that in tables 4.1 to 4.3 the SIMM values are identical. This is because SIMM is a symmetric model, charging the same IM for both sides of the swap. From the resulting figures that summarise these tables it is clear that the CCP model captures a tail risk that is clearly non-symmetrical. The bar graphs in this section therefore display the REC and PAY side of the swaps as well as their average to be compared to the SIMM values. Further note that since no concentration risks nor correlations are taken into account in this analysis the SIMM values are simply the risk weights given for the respective risk buckets.

Table 4.1: **REC**: Receiving floating and paying fixed isolated exposure swap IM values as a percentage of unit exposure. The results from the FHS ES h-day models at various levels of α and SIMM version 2.2 and 2.3, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights are given.

α	97.5%			99%			99.75%			SIMM			
h	5-day	10-day	15-day	5-day	10-day	15-day	5-day	10-day	15-day	SA v2.2	SA v2.3	UK v2.2	UK v2.3
Average	33.44	46.98	59.11	47.63	62.16	78.37	73.77	87.69	119.80	94.67	92.25	68.00	68.08
2W	60.02	77.84	94.78	93.57	108.79	132.13	152.51	154.53	202.21	85.00	103.00	116.00	114.00
1M	38.85	51.12	67.26	66.33	76.14	103.47	119.28	115.34	198.45	80.00	96.00	106.00	107.00
3M	40.17	52.61	65.64	68.32	76.44	98.63	122.84	121.14	190.09	79.00	84.00	94.00	95.00
6M	38.74	48.19	61.31	68.89	73.41	92.82	127.77	117.00	157.73	86.00	84.00	71.00	71.00
1Y	24.86	37.13	44.96	35.16	53.04	63.10	58.07	85.60	102.92	97.00	89.00	59.00	56.00
2Y	29.03	44.03	53.80	37.85	58.12	68.85	54.81	80.68	96.46	102.00	87.00	52.00	53.00
3Y	27.83	42.11	52.13	34.21	51.87	63.10	44.41	68.00	82.73	104.00	90.00	49.00	50.00
5Y	28.06	42.06	53.10	33.76	49.85	62.98	42.58	64.11	82.12	102.00	89.00	51.00	51.00
10Y	28.40	42.46	53.73	33.44	50.21	63.17	40.73	61.22	77.92	103.00	90.00	51.00	53.00
15Y	26.65	40.50	52.06	31.26	47.65	61.20	38.23	60.00	76.77	99.00	99.00	51.00	50.00
20Y	27.68	41.28	53.10	32.35	48.22	61.95	39.69	59.45	79.04	99.00	100.00	54.00	54.00
30Y	30.95	44.44	57.48	36.38	52.12	69.06	44.35	65.22	91.20	100.00	96.00	62.00	63.00

Table 4.2: **PAY**: Paying floating and receiving fixed isolated exposure swap IM values as a percentage of unit exposure. The results from the FHS ES h-day models at various levels of α and SIMM version 2.2 and 2.3, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights are given.

α	97.5%			99%			99.75%			SIMM			
h	5-day	10-day	15-day	5-day	10-day	15-day	5-day	10-day	15-day	SA v2.2	SA v2.3	UK v2.2	UK v2.3
Average	27.98	41.58	50.95	39.45	57.17	69.71	62.88	89.78	108.53	94.67	92.25	68.00	68.08
2W	32.36	42.74	48.28	43.36	52.62	60.09	55.16	67.72	77.79	85.00	103.00	116.00	114.00
1M	17.28	30.39	39.07	33.85	52.20	65.95	65.85	96.45	124.77	80.00	96.00	106.00	107.00
3M	18.75	32.26	39.04	37.18	53.07	65.62	70.19	96.07	118.33	79.00	84.00	94.00	95.00
6M	16.26	22.58	25.27	22.37	31.89	35.11	35.03	50.88	53.12	86.00	84.00	71.00	71.00
1Y	25.76	36.69	43.26	37.76	54.92	63.92	69.64	104.20	117.43	97.00	89.00	59.00	56.00
2Y	29.79	43.14	52.99	40.99	60.27	73.42	68.60	102.54	118.61	102.00	87.00	52.00	53.00
3Y	30.22	44.64	55.38	40.67	60.08	74.17	63.20	95.67	117.49	104.00	90.00	49.00	50.00
5Y	31.50	47.43	58.37	41.81	63.08	76.62	65.54	92.75	114.40	102.00	89.00	51.00	51.00
10Y	33.47	49.30	61.92	43.56	64.04	79.96	63.29	93.73	115.34	103.00	90.00	51.00	53.00
15Y	30.77	46.63	58.36	40.27	60.53	75.57	60.94	87.01	109.10	99.00	99.00	51.00	50.00
20Y	32.75	49.42	62.79	43.09	64.40	80.81	64.95	93.71	113.93	99.00	100.00	54.00	54.00
30Y	36.87	53.68	66.62	48.54	68.94	85.34	72.15	96.61	122.04	100.00	96.00	62.00	63.00

Since the SIMM is calibrated for a 10-day 99% risk level, the first and most important comparison is to look at the FHS result for the 10-day 99% α level, and compare it to the SIMM values for versions 2.2 and 2.3 for high-volatility currencies. This comparison is given as a bar plot in figure 4.1, which gives the estimated ES values at each tenor. These values are given for the REC side and PAY side, as well as their average. The SIMM values are also given for high-volatility currencies (SA) risk

Table 4.3: **AVERAGE**: Average of REC (4.1) and PAY (4.2) swaps IM values as a percentage of unit exposure. The results from the FHS ES h-day models at various levels of α and SIMM version 2.2 and 2.3, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights are given.

α	97.5%			99%			99.75%			SIMM			
h	5-day	10-day	15-day	5-day	10-day	15-day	5-day	10-day	15-day	SA v2.2	SA v2.3	UK v2.2	UK v2.3
Average	30.71	44.28	55.03	43.54	59.66	74.04	68.32	88.74	114.17	94.67	92.25	68.00	68.08
2W	46.19	60.29	71.53	68.46	80.71	96.11	103.84	111.13	140.00	85.00	103.00	116.00	114.00
1M	28.06	40.75	53.17	50.09	64.17	84.71	92.57	105.90	161.61	80.00	96.00	106.00	107.00
3M	29.46	42.43	52.34	52.75	64.76	82.13	96.51	108.61	154.21	79.00	84.00	94.00	95.00
6M	27.50	35.39	43.29	45.63	52.65	63.96	81.40	83.94	105.43	86.00	84.00	71.00	71.00
1Y	25.31	36.91	44.11	36.46	53.98	63.51	63.85	94.90	110.17	97.00	89.00	59.00	56.00
2Y	29.41	43.59	53.40	39.42	59.20	71.13	61.70	91.61	107.53	102.00	87.00	52.00	53.00
3Y	29.03	43.38	53.76	37.44	55.98	68.64	53.80	81.84	100.11	104.00	90.00	49.00	50.00
5Y	29.78	44.75	55.74	37.79	56.46	69.80	54.06	78.43	98.26	102.00	89.00	51.00	51.00
10Y	30.93	45.88	57.83	38.50	57.13	71.56	52.01	77.47	96.63	103.00	90.00	51.00	53.00
15Y	28.71	43.56	55.21	35.77	54.09	68.39	49.58	73.51	92.94	99.00	99.00	51.00	50.00
20Y	30.21	45.35	57.94	37.72	56.31	71.38	52.32	76.58	96.48	99.00	100.00	54.00	54.00
30Y	33.91	49.06	62.05	42.46	60.53	77.20	58.25	80.92	106.62	100.00	96.00	62.00	63.00

weights and regular currencies (UK) risk weights. The former is used for the primary comparisons and the latter is more for supplementary analysis. Note that the only difference between the SA values and the UK values are the risk weights used in the SIMM calculation. The left most bars represent the average IM as a percentage of PV01 exposure across all tenors in figure 4.1. There would be major concern if the SIMM versions 2.2 and 2.3 values for high-volatility currencies were consistently lower than the FHS values across the tenors, however it appears that the SIMM has adequate risk coverage for its specified calibration. The only exception is at the 2W tenor, where the REC side of the FHS model surpasses the SIMM initial margins. The distribution for this rate is investigated later in this section to explain this apparent skewness. The average of the two sides for this tenor is still below the relevant SIMM values, so there is no concern with regard to the risk specification of the SIMM for isolated exposures at each tenor. The average across tenors show that the SIMM is more than adequate on average for the given risk calibration.

From the bar plot in figure 4.1 it is clear that there is asymmetry with regard to the tail risk for the exposures. The 2W through 6M rates have the REC side larger than the PAY side, in other words those with long short-term exposures are more exposed than those with short short-term exposures to the relevant rates. The opposite case is true for the rates 1Y through 30Y, where the PAY side is larger. One should take note of this asymmetry as it may play a role in subsequent analysis.

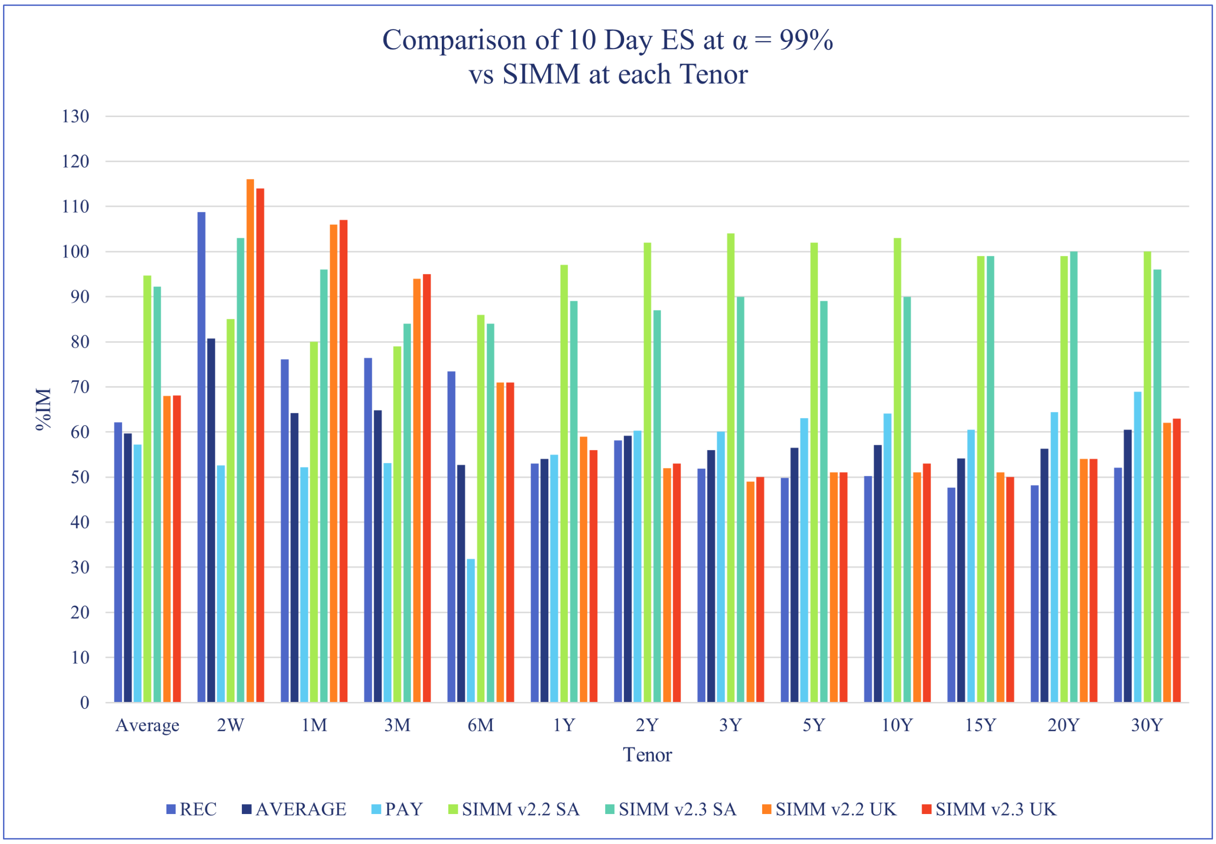


Figure 4.1: A bar plot of the IM values as a percentage of the PV01 exposure for isolated exposures at each tenor. The plot includes the ES values obtained for the 10 day FHS model at the 99% confidence level for isolated positive exposures (REC), negative exposures (PAY) and their average at each tenor. For comparison the plot includes the SIMM version 2.2 and version 2.3 values for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights. The left-most bars represent the average values across all tenors.

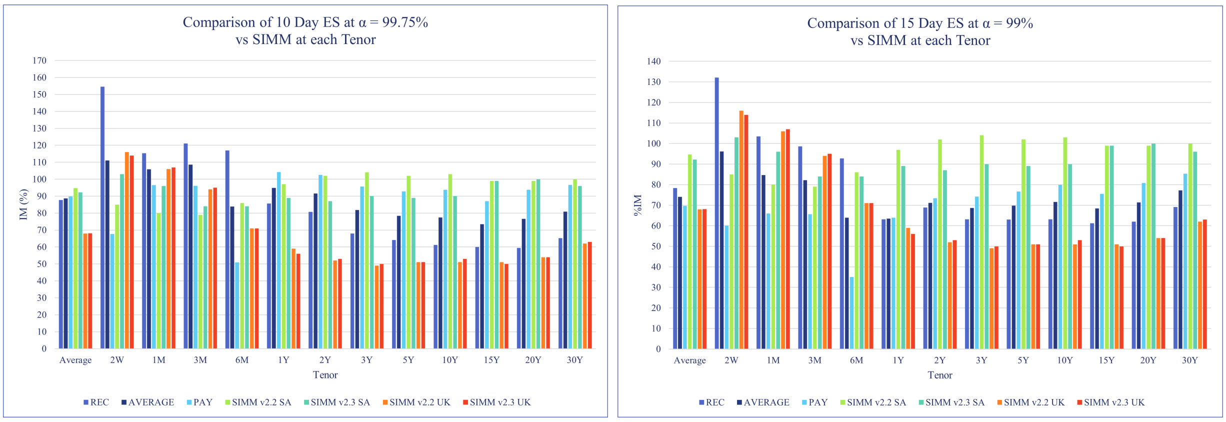
It is also clear from the tables and figure 4.1 in particular that the normal currency risk weights are clearly not appropriate for the margins required in this market. The FHS model shows consistent breeches of the SIMM UK values for version 2.2 and 2.3 at most of the the tenors. Looking at the distribution of risk weights for regular currenices and high-volatility currencies it is clear that they differ with regard to their shape and size. The high-volatility risk weights, clearly the appropriate choice, is the focus of further discussion.

The plots of IM for different risk metrics, namely 10-day at $\alpha = 99.75\%$ and 15-day at 99%, are given in figures 4.2a and 4.2b respectively. In these plots the SIMM values are the same as in figure 4.1, so these figures allow for additional assessment of the relevant risk coverage of the SIMM. Results in figure 4.2a show the ES estimates for a much higher quantile, the 99.75% level, showing the average of only the most extreme simulated 10-day returns. One can see that from this plot as well as tables 4.1 to 4.3, that all these estimates are greater than the 10-day 99% estimates by a factor of approximately 1.49 on average. It is clear that for the 2W through 6M rates the ES estimates are larger than the SIMM values, but for the longer term rates the SIMM still appears to cover this risk when looking at the average of the two sides.

Figure 4.2b shows the results for ES estimates at the 15-day risk horizon at the 99% confidence level. This is relevant for assessing the risk over a longer MPR than the 10 days used to calibrate the SIMM. With the exception of the REC 2W rate the SIMM values for high-volatility currencies gives adequate risk coverage for both of the versions presented here. Only at the 15-day 99.75% level will one start to see some consistent breaches of the SIMM values, which becomes evident when investigating some of these results individually.

To gain an in depth look at the tail risks captured by the FHS model, one needs to focus on individual tenors at the different risk specifications. To limit the scope only some key tenors are analysed, namely the 2W, 6M, 5Y and 30Y rates. These are chosen based on the plots in figures 4.1, 4.2a and 4.2b, which show these tenors to be worth investigating. The 2W and 6M rates can be seen as representative of the short end of the curve and the 5Y and 30Y more representative of the mid to long ends.

Firstly, figure 4.3 shows the results summarised for the average IM values across all risk metrics. For this comparison and subsequent displays, figures 4.4 to 4.7, the SIMM values worth noting are



(a) 10-day 99.75%

(b) 15-day 99%

Figure 4.2: Bar plots of the IM values as a percentage of the PV01 exposure for isolated exposures at each tenor. The plot includes the ES values obtained for the FHS model at two different risk calibrations for isolated positive exposures (REC), negative exposures (PAY) and their averages at each tenor. For comparison the plots include the SIMM version 2.2 and version 2.3 values for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights. The left-most bars represent the average values across all tenors.

the two versions for high-volatility currencies (orange and dark orange). Only the 15-day 99.75% risk calibration appears to consistently breach the SIMM thresholds, for PAY and REC sides. On average the high-volatility SIMM is larger for all other risk calibrations. Note that the SIMM is on average approximately 1.57 times greater than the 10-day 99% ES obtained by the FHS model.

Now taking a closer look at the results for the 2W tenor in figure 4.4, there are several breeches of the SIMM at various risk calibrations. Considering the 10-day 99% ES estimate, it is still larger than the SIMM calculations when looking at the average of PAY and REC sides. Here the REC side is much larger than the PAY side, and the 10-day 99% ES REC side estimate breeches both the relevant SIMM values.

The skewness of these estimates is evident from the 10-day simulated distribution for this rate in figure 4.8a. There is a considerable left-skew in the simulated returns used to make the ES estimates. This helps explains the asymmetry of the results when also looking at the daily returns in figure 4.9a. Here one can see that the sample contains much larger decreases than increases, and it is the re-sampling of these large values (after standardisation) that inflates the one end more than the other.

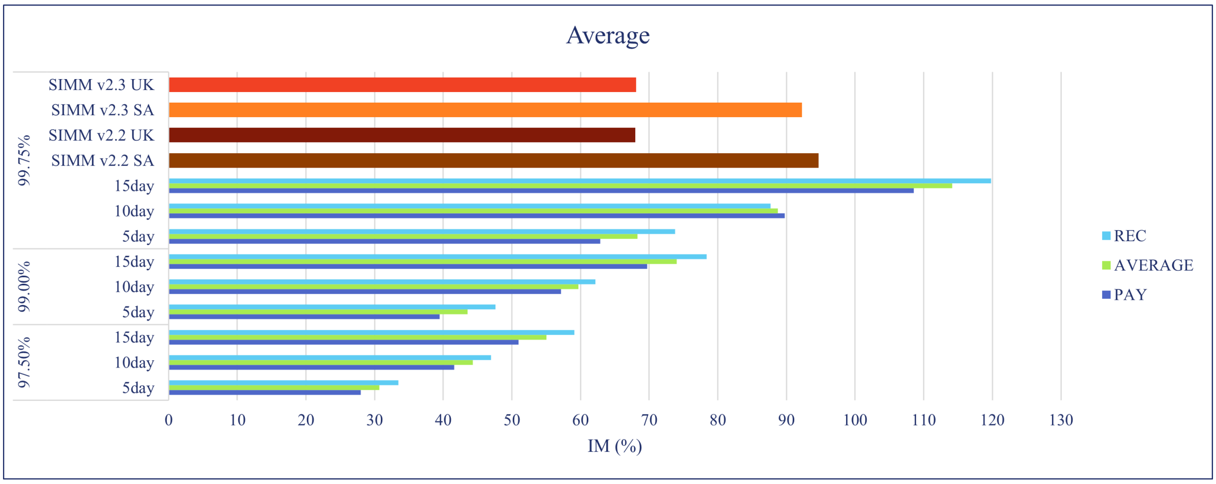


Figure 4.3: A horizontal bar plot of the average IM as a percentage of PV01 exposure averaged across all tenors for REC and PAY swaps and their averages. The average h-day ES FHS values are given for various values of α, and compared to the average SIMM values across all tenors for versions 2.2 and 2.3, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights.

The values obtained are also very large since the volatility estimate used to initialise the simulations is larger than all the other tenor volatility estimates. This can be seen in table 4.5, in the third row. The reason for this is a large persistence (β) parameter estimate, shown in table 4.4, meaning that the volatility persists in the market for a long time following a market shock. Note that in table 4.5, the 2W rate is the only rate for which the annualised long term unconditional volatility estimate is larger than the current annualised estimate for all the tenors that have tractable long term estimates based on their estimates in table 4.4.

Table 4.4: Estimated GARCH(1, 1) parameters of the relevant tenors of the South African Swap Index Curve.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
$\hat{\omega}$	0.332	0.968	0.864	0.532	2.210	3.384	3.113	3.121	3.472	3.318	3.573	3.557
$\hat{\alpha}$	0.023	0.161	0.172	0.162	0.323	0.236	0.162	0.149	0.125	0.140	0.138	0.136
$\hat{\beta}$	0.960	0.839	0.828	0.838	0.554	0.650	0.751	0.783	0.801	0.789	0.789	0.792

The results for the 6M tenor are given in figure 4.5. This rate only breeches the SIMM at the 15-day 99.75% calibration when looking at the average of the REC and PAY sides. Here the REC side is larger than the PAY side, with the REC side showing larger values than the relevant SIMMs for four of the calibrations. The 10-day 99% ES estimate is covered by the SIMM for the REC and

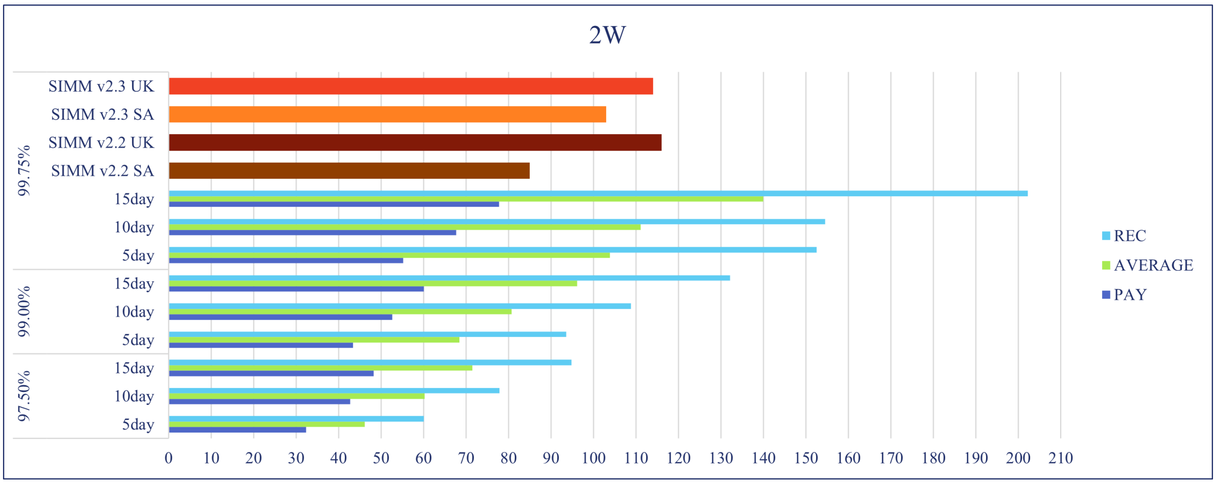


Figure 4.4: A horizontal bar plot of the IM as a percentage of PV01 exposure of an isolated exposure at the 2W tenor for REC and PAY swaps and their averages. The h-day ES FHS values are given for various values of α, and compared to the SIMM version 2.2 and version 2.3 values, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights.

Table 4.5: Various annualised volatility estimates in basis points for each tenor.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
LT Unconditional vol. (GARCH)†	70.19	-	-	-	67.11	86.15	94.39	107.06	108.42	108.12	110.07	111.22
ST DEV	89.58	78.53	77.92	64.54	57.53	75.54	90.96	110.79	119.24	117.69	117.95	120.64
Conditional vol. (GARCH)	92.43	56.58	60.75	59.74	46.36	66.18	68.60	75.28	82.00	75.88	78.69	84.34

† When the estimated $\hat{\alpha} + \hat{\beta} \approx 1$, then the LT unconditional volatility cannot be estimated.

PAY sides.

Note an anomaly that appears for the 99.75% estimates at the 5-day and 10-day calibration. Here the 5-day ES estimate is larger than the 10-day estimate. This is possible since the 5-day simulations and 10-day simulations are run independently, but could also happen in some simulations regardless. This phenomenon only occurs at this α level, meaning that there could be very some large 5-day return simulations that get more weight in the ES estimate as the significance level increases. This occurs for the REC sides of the 1M and 3M rates as well.

The results of the 6M rate also shows asymmetry, which can be seen from the histogram of the simulated distribution in figure 4.5. There is a considerable left skew in the simulated data in figure 4.9b, which is also present in the historical 10 year sample (not shown here). The volatility of this rate used for the simulation is 59.74 basis points in annualised terms in table 4.5, however a long term estimate cannot be obtained from the estimated GARCH parameters.

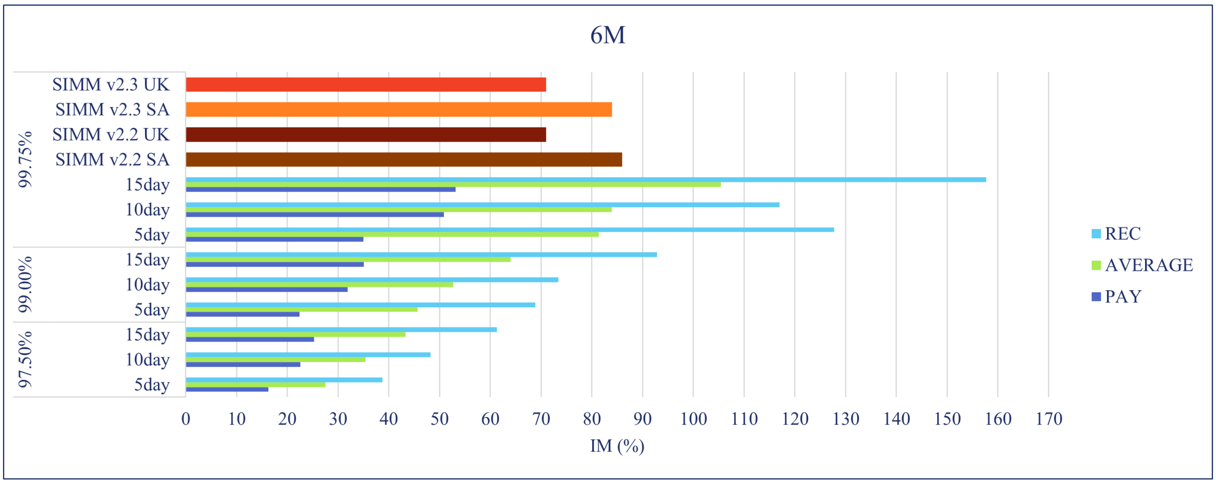


Figure 4.5: A horizontal bar plot of the IM as a percentage of PV01 exposure of an isolated exposure at the 6M tenor for REC and PAY swaps and their averages. The h-day ES FHS values are given for various values of α, and compared to the SIMM version 2.2 and version 2.3 values, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights.

For both the 5Y and 30Y results, the only risk calibration that leads to concern is the 15-day 99.75% level. Here the PAY side is larger than the REC side in contrast to the previous comparisons. This is also evident from the simulated distributions in figures 4.8c and 4.8d, where the histograms show a right skew. The distributions are less leptokurtic and more symmetrical than the distributions for the 2W and the 6M rates.

The conditional GARCH volatilities of the rates at the long end of the curve, like the 5Y and 30Y rates, have higher estimates than the short end (except 2W). This tendency is also reflected in SIMM where the risk weights are higher for the longer rates than the shorter ones, with the exception of the 2W rate. This is also reflected in the IM values obtained when looking at the 10-day 99% average IM, which is 56.46% for the 5Y rate and 60.53% for the 30 year rate, in table 4.3. These are both larger than the 52.65% estimate of the 6M rate.

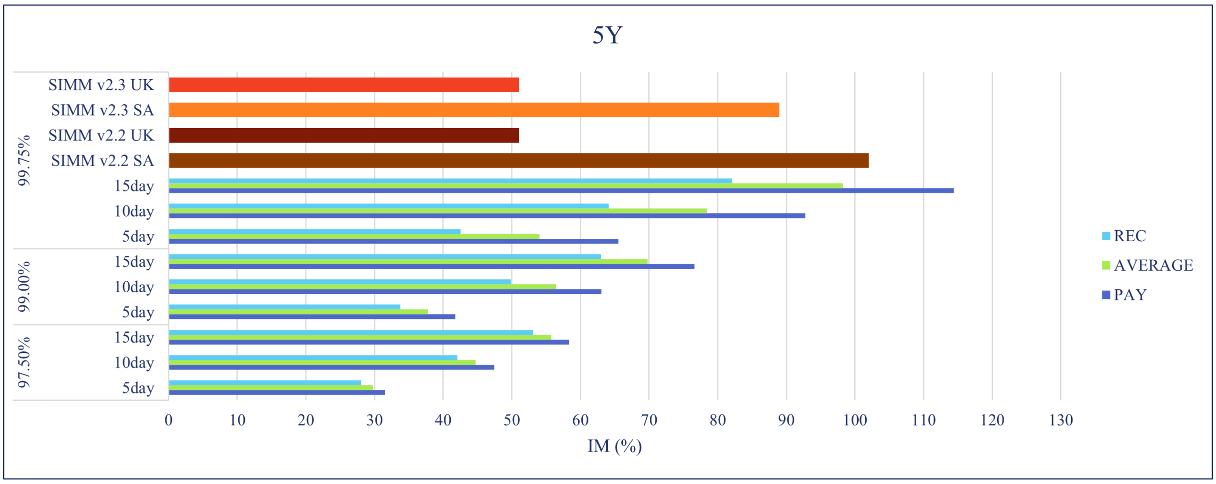


Figure 4.6: A horizontal bar plot of the IM as a percentage of PV01 exposure of an isolated exposure at the 5Y tenor for REC and PAY swaps and their averages. The h-day ES FHS values are given for various values of α, and compared to the SIMM version 2.2 and version 2.3 values, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights.

Table 4.5 also includes the standard deviation of the daily returns of the various rates for a sample of 750 days (three years). This is not meant to be compared to the GARCH estimates on absolute terms, as the estimation is based fundamentally on different assumptions. The standard deviation estimate is presented so that it can supplement the trend that the volatility's on the long end are higher than the short end. This trend is also evident in the SIMM risk weight calibration for the high-volatility currencies. However, this trend is not necessarily reflected with the IM values obtained. The 1M and 3M IM values are higher at the 10-day 99% level, with 64.17% and 64.76% respectively, than all the other rates (except 2W) in table 4.3.

It appears that although the SIMM adequately covers the risks at the required calibration, it is apparent from figure 4.1 that the same trend for the two models is not necessarily guaranteed. For example, the differences between SIMM version 2.3 and the 10-day 99% ES estimate are greater at

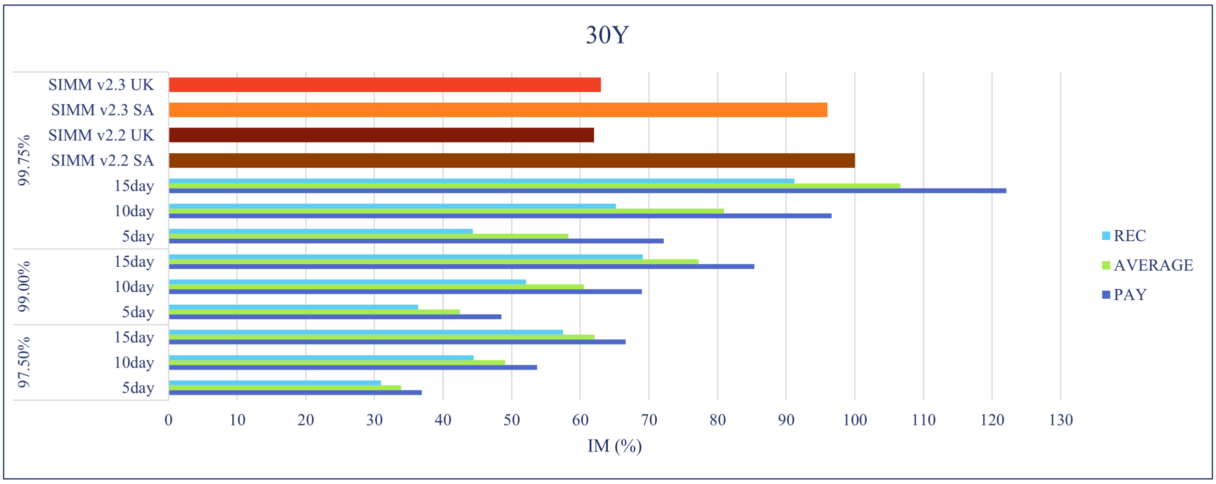
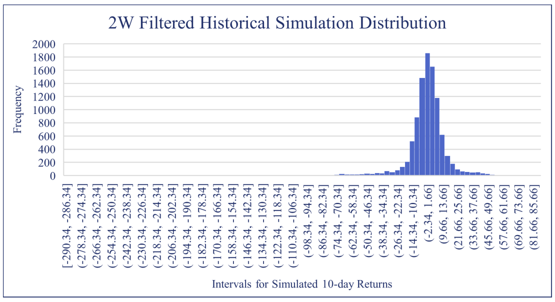
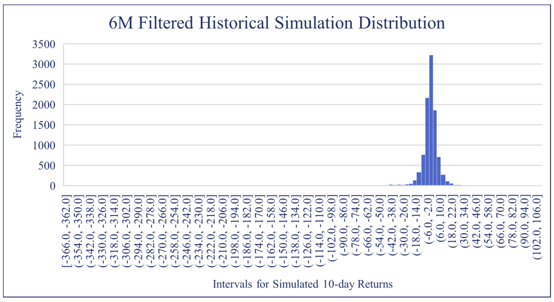


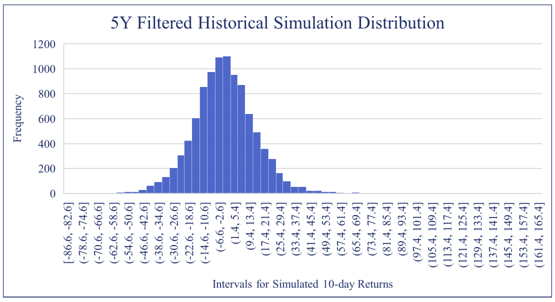
Figure 4.7: A horizontal bar plot of the IM as a percentage of PV01 exposure of an isolated exposure at the 30Y tenor for REC and PAY swaps and their averages. The h-day ES FHS values are given for various values of α, and compared to the SIMM version 2.2 and version 2.3 values, for high-volatility currencies (SA) risk weights and regular currencies (UK) risk weights.



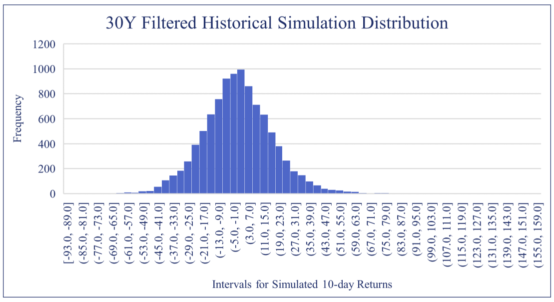
(a) 2W



(b) 6M

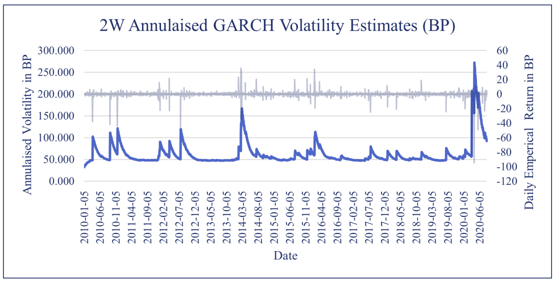


(c) 5Y

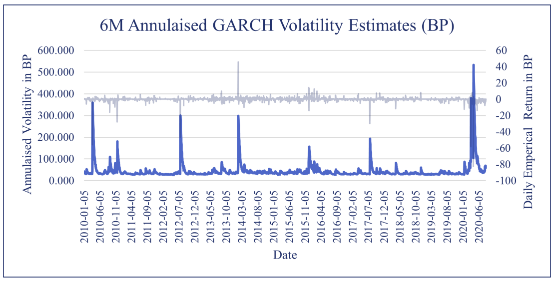


(d) 30Y

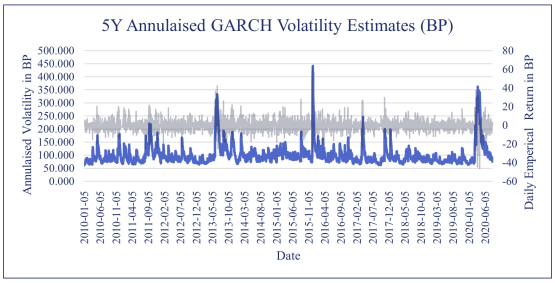
Figure 4.8: Histograms representing the 10-day FHS simulations that are generated for four of the tenors. The left tails of these distributions represents the risks for the long exposures (REC) and the right tails represent the exposure to the short side (PAY).



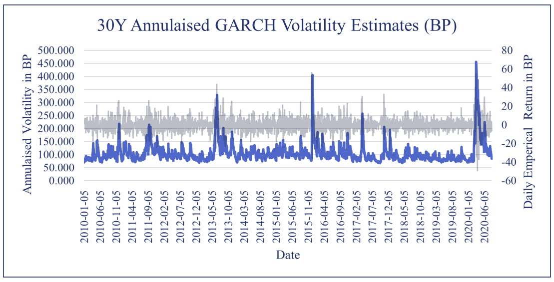
(a) 2W



(b) 6M



(c) 5Y



(d) 30Y

Figure 4.9: Time series plots of the estimated GARCH$(1,1)$ annualised volatilities for four of the tenors at each day of the sample. Superimposed are the empirical daily returns with a separate axis on the right of the graphs.

the long end than the short end, reflecting a larger potential for risk on the short end. Further, the IM as a percentage of exposure is larger for the long ends of the SIMM compared to the short ends, however the opposite is apparent with the ES estimates. This phenomenon could present itself again in subsequent sections.

The risk weights of the SIMM model are investigated by comparing them to a market-calibrated FHS model. By applying portfolios PV01 profiles with unit exposure at each tenor, results are produced for both models that represent the IM as a percentage of exposure. This allows for a comparable way of conducting the analysis. It is clear that the SIMM versions 2.2 and 2.3 for high-volatility currencies are able to adequately cover the 10-day 99% risk specification. This indicates that the SIMM risk weights are more than adequate when looking at isolated exposures. Although this section gives an in depth look at the risks in isolation, more analysis is required to investigate the interactions between these risk weights which includes an assessment of the adequacy of the calibrated correlations of SIMM.

4.3 RESULTS OF STANDARDISED COMPARISONS

This section discusses the results obtained from employing the novel methodology described in section 3.4. The results are given in tables 4.6 to 4.14, which show the IM as a percentage of the absolute exposure of the various profiles. The profiles are given in tables 3.3 to 3.7 in section 3.4, where figures are given in order to visualise the shapes. These tables and figures should be used in conjunction with the tables and graphs in this section to gain additional understanding of the model risks.

Flat Profiles

The first set of profiles to look at are the flat profiles. That is the LO profile, with unit PV01 exposure at each of the tenors and SO profile with unit negative PV01 exposure at each tenor. Table 4.10 gives the results for these profiles for various risk calibrations. From this table and figure 4.10, which gives a summary of the results for the 10-day and 15-day 99% calibrations, the SIMM is able to comfortably cover the risks for both the LO and SO sides for both the calibrations shown in the figure.

Table 4.6: **Flat**: IM as a percentage of absolute PV01 exposure for the flat profiles (3.1). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO and SO variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

α	97.5%			99%			99.75%			SIMM	
	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	23.80	33.89	40.80	31.65	43.78	51.65	45.22	64.98	74.03	75.00	71.90
SO	22.03	31.76	42.11	28.74	41.99	57.32	42.35	65.10	86.11	75.00	71.90

The results of this comparison are fairly symmetric, the FHS results do not differ substantially for the LO and SO shapes. The results obtained in the previous section showed major skewness in the IM results depending on whether one was long or short. It was noted that the short end of the curve showed higher IM for the long exposures and the opposite was true for the tenors at the long end. The results here show that a flat PV01 profile effectively balances out this asymmetry.

There appears to be a diversification benefit evident in both the SIMM models and the FHS models. Looking at the average IM over all the tenors in table 4.3 for the 10-day 99% calibration, one sees

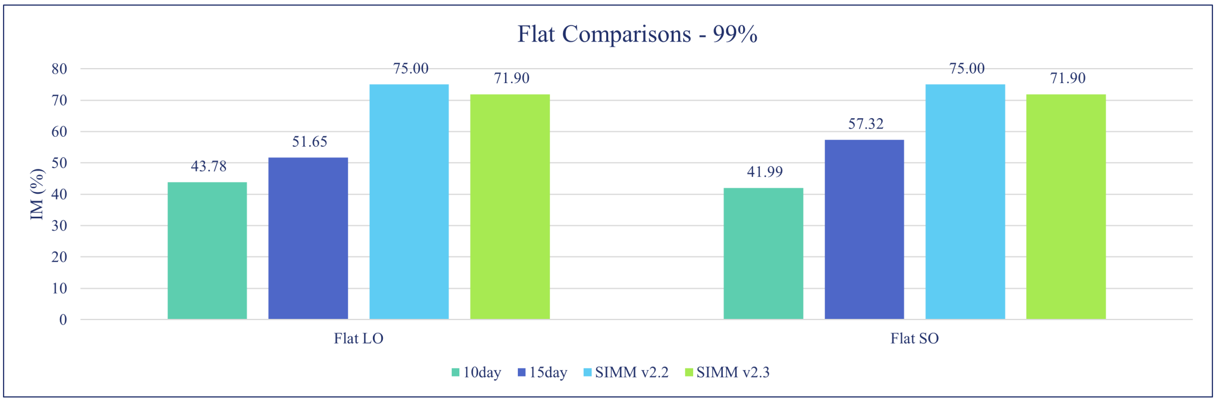


Figure 4.10: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **flat** profiles.

that the 59.6% is larger than the 43.78% and 41.90% obtained for the LO and SO comparisons respectively. The average SIMM version 2.3 value is 92.25% and the results here show 71.90% for a flat profile. This shows an approximate diversification benefit for the FHS model in this case to be a factor of 1.39 whereas the benefit factor for the SIMM model is 1.28. Therefore, although very slightly, the FHS model gives a higher diversification benefit in relative terms. These benefits result from including interactions between the risk factors, rather than looking at the risk factors in isolation.

These results help show the diversification effect when giving equal balance to all the risk factors, which is not necessarily representative of a realistic portfolio, but is a good place to start when assessing various other profile shapes. Another relevant comparison to do initially is to see how the results compare for the short end of the curve versus the long end. These two results equip one with enough information to conduct analysis on profiles that have non-flat structures.

ST vs LT Profiles

The ST (short-term) versus LT (long-term) comparison results, in table 4.7 and summarised in figure 4.11, further show the skewed distributions apparent in antecedent analyses. The ST LO profiles have unit positive PV01 exposure from the 2W tenor through to the 2Y tenor. The ST SO has the negative exposures at those tenors, as in table 3.2. The 10-day 99% IM for the LO is 64.57% whereas the value for the SO profile is 29.43% in comparison to 75.12% of SIMM version 2.3. Therefore there is a tremendous difference in the risks for the two parties in ST swap trades in

SA. Fortunately the SIMM IM is sufficient to cover this risk.

Table 4.7: **ST versus LT**: IM as a percentage of absolute PV01 exposure for the ST vs LT profiles (3.2). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO, SO and LS variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	ST	32.72	44.71	52.89	50.22	64.57	72.38	74.72	101.29	113.57	72.83	75.12
	LT	28.96	42.86	54.19	34.16	52.14	64.83	42.29	70.78	83.38	97.41	90.53
SO	ST	17.02	22.14	27.00	23.53	29.43	36.68	34.25	40.19	58.15	72.83	75.12
	LT	34.20	50.29	66.28	43.94	65.84	88.89	63.02	99.52	133.53	97.41	90.53
L-S	ST	18.97	26.56	32.93	25.67	35.70	43.74	36.77	56.22	67.49	42.11	41.84
	LT	12.95	18.58	23.45	16.17	22.64	28.44	22.27	30.14	38.92	42.11	41.84

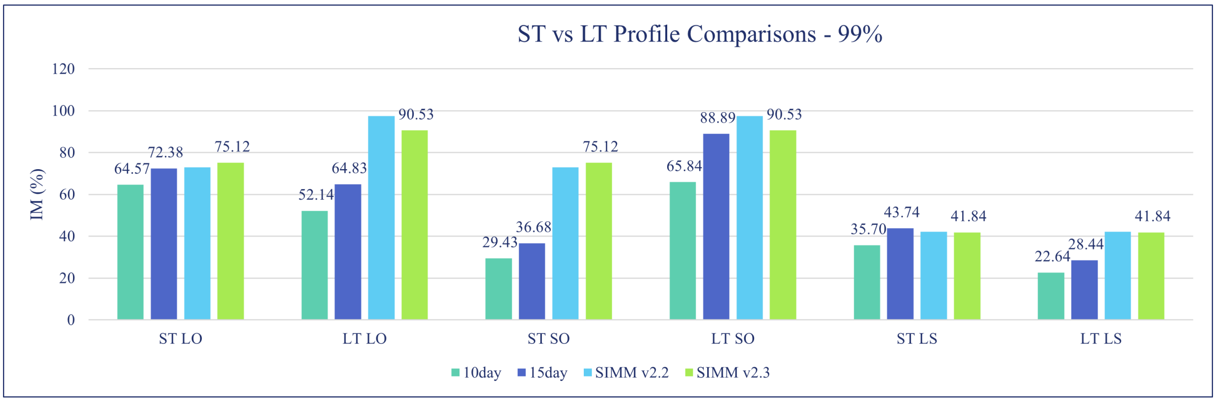


Figure 4.11: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **ST vs LT** profiles.

The LT profiles, have the same form as the ST, but with exposures at the 3Y through 30Y tenors. Here the skew is in the opposite direction as alluded to from the flat comparisons. The SIMM version 2.3 value of 90.53% is higher than both the respective LO and SO values of 52.14% and 65.84%. It is already apparent from figure 4.1 that the SIMM has relatively higher risk weights for the individual LT tenors than the ST ones compared to the FHS values. The skew in the results are also already apparent in this figure, therefore the result here behave as expected.

It is interesting to note that the SIMM values for version 2.3 are higher than those for version 2.2 for the ST comparison. The SIMM has increased from 72.83% to 75.12%, which is perhaps due to the newer calibration showing the higher volatility in the ST rates seen in the recent market. For the LT comparison, the opposite occurs, with SIMM decreasing the IM required for this analysis from 97.41% for version 2.2 to 90.53% for version 2.3. Here the SIMM for the LT is higher than the ST, however the opposite trend appears in the 10-day 99% FHS ES case. The IM is more prudent for LT exposures than ST exposures for South African swaps according to SIMM.

There is still much to be said regarding the LS profiles. The profile called ST LS contains positive exposures for the tenors 2W through 2Y and negative exposures in the rest. The LT LS profile has the negative of this exposure, and thus allowing insight into influence of correlations in the face of the imbalance of the results for long and short exposures. This is the first comparison that includes both positive and negative exposures in the same profile, which creates significant diversification benefits in both models. In the SIMM this is a result of the strong correlations among rates, hence the positive and negative values create cancellation effects.

Correlation Comparisons

Although the FHS model and the SIMM are based on different assumptions regarding their correlation structure, it is worth comparing the correlations presented in the SIMM framework (tables 2.3 and 2.4) with the estimated correlations of the daily returns and the FHS 10-day simulations. Some remarks need to be made here before continuing with the analysis, but the discussion is limited to a few tenors as to not distract from the aims of this section.

The correlation estimates for the daily returns, in table 4.8, and the correlations of the FHS simulated 10-day returns, in table 4.9, gives one an indication of how the tenor rates interact in the FHS model. Notice that the 1-day correlations are more pronounced than the 10-day correlations in the simulated sample.

Comparing the SIMM version 2.3 correlations from table 2.4 with the 10-day correlations (table 4.9) at some of the tenors can help explain the results that have been seen so far and enriches the forthcoming analysis. Firstly notice the correlations of the 2W rate, for the 10-day simulations have higher positive correlations for the 3M rate than the SIMM correlations. The 2W correlation with the 1M and 6M rates for the 10-day simulation are less than those for SIMM. The FHS model shows zero to almost zero correlations with the 1Y through 30Y, with some small negative correlation at the LT tenors. SIMM, in comparison, has fairly generous correlations for the 2W with these rates.

One should note that the correlations in the FHS model may be more pronounced for the returns produced at high quantiles, such as the 99% level and will depend on the portfolio in question. Therefore one should be careful not to look too deeply into these estimated correlations, as they are simply meant to supplement the analysis conducted here.

Consider the 1Y correlations in table 4.9, apart from the ST tenors the correlations are fairly consistent with the SIMM correlations. The same can be said when looking at the correlations of the 30Y tenor with the rates at the longer maturity. The LT tenors appear to have similar correlations with the SIMM. Therefore it is the correlations of the ST tenors with the LT tenors that is expected to influence the difference in the results of the two models in this section.

Table 4.8: Daily return correlations estimated as the linear correlation among the tenor rates of the South African Swap Index curve over a sample of the past three years (750 trading days) data.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
2W	1.00	0.87	0.87	0.77	0.25	0.05	0.02	0.02	-0.02	-0.03	-0.04	-0.02
1M	0.87	1.00	0.99	0.92	0.28	0.05	0.03	0.02	-0.03	-0.04	-0.05	-0.04
3M	0.87	0.99	1.00	0.92	0.28	0.05	0.03	0.02	-0.04	-0.05	-0.05	-0.04
6M	0.77	0.92	0.92	1.00	0.34	0.11	0.08	0.04	-0.02	-0.03	-0.04	-0.04
1Y	0.25	0.28	0.28	0.34	1.00	0.92	0.83	0.62	0.43	0.43	0.42	0.41
2Y	0.05	0.05	0.05	0.11	0.92	1.00	0.92	0.76	0.60	0.60	0.60	0.59
3Y	0.02	0.03	0.03	0.08	0.83	0.92	1.00	0.88	0.75	0.74	0.74	0.73
5Y	0.02	0.02	0.02	0.04	0.62	0.76	0.88	1.00	0.94	0.92	0.91	0.91
10Y	-0.02	-0.03	-0.04	-0.02	0.43	0.60	0.75	0.94	1.00	0.98	0.97	0.97
15Y	-0.03	-0.04	-0.05	-0.03	0.43	0.60	0.74	0.92	0.98	1.00	0.99	0.97
20Y	-0.04	-0.05	-0.05	-0.04	0.42	0.60	0.74	0.91	0.97	0.99	1.00	0.98
30Y	-0.02	-0.04	-0.04	-0.04	0.41	0.59	0.73	0.91	0.97	0.97	0.98	1.00

Looking again at the ST versus LT comparisons, but now at the LS comparisons, one can see that the ST LS profile results in higher IM relative to SIMM than the LT LS profile, when looking at the 10-day 99% estimates. This is because these profiles accentuate the skewed phenomena detected so far. Hence the ST LS profile is higher than the SIMM's 41.84% at the 15-day 99% calibration with 43.74%. This is perhaps also a result of the low correlations among ST and LT rates in the FHS model, which is evident from the correlation comparison. The SIMM therefore gives greater diversification benefit in the ST LS case.

Table 4.9: FHS 10-day simulation correlations estimated as the linear correlation among the volatility-scaled simulated tenor rates of the South African Swap Index curve which consists of 10 000 simulated 10-day returns.

	2W	1M	3M	6M	1Y	2Y	3Y	5Y	10Y	15Y	20Y	30Y
2W	1.00	0.67	0.66	0.51	0.08	0.03	0.01	0.00	0.00	-0.01	-0.02	-0.01
1M	0.67	1.00	0.98	0.72	0.06	0.03	0.02	0.02	0.02	0.01	0.01	0.01
3M	0.66	0.98	1.00	0.74	0.07	0.02	0.02	0.02	0.01	0.00	0.00	0.00
6M	0.51	0.72	0.74	1.00	0.18	0.15	0.14	0.12	0.10	0.10	0.10	0.09
1Y	0.08	0.06	0.07	0.18	1.00	0.92	0.84	0.75	0.68	0.67	0.68	0.66
2Y	0.03	0.03	0.02	0.15	0.92	1.00	0.93	0.86	0.80	0.80	0.79	0.78
3Y	0.01	0.02	0.02	0.14	0.84	0.93	1.00	0.94	0.89	0.88	0.88	0.86
5Y	0.00	0.02	0.02	0.12	0.75	0.86	0.94	1.00	0.95	0.94	0.94	0.93
10Y	0.00	0.02	0.01	0.10	0.68	0.80	0.89	0.95	1.00	0.96	0.96	0.95
15Y	-0.01	0.01	0.00	0.10	0.67	0.80	0.88	0.94	0.96	1.00	0.98	0.96
20Y	-0.02	0.01	0.00	0.10	0.68	0.79	0.88	0.94	0.96	0.98	1.00	0.97
30Y	-0.01	0.01	0.00	0.09	0.66	0.78	0.86	0.93	0.95	0.96	0.97	1.00

Linear Profiles

The linear profiles gives linearly increasing weight at each tenor. The increasing LO and decreasing SO profiles are to be compared together, as the profiles represent opposite ends of the distribution for such a portfolio. In this case the decreasing SO profile obtains 58.37% and the increasing LO obtains 46.99% at the 10-day 99% quantile, in table 4.10 and figure 4.12. These values are still well below the SIMM version 2.3 requirement of 83.17%. These profiles put more weight on the end of the curve than in the beginning, so this comparison informs one of the relative risks of a portfolio with LT exposures. For this particular comparison the skew is not as pronounced as the with the ST vs LT comparisons. This is because it does not give heavy weights to the ST tenors, where much of the skewness is present.

The decreasing LO and increasing SO comparisons look at exposures weighted more heavily toward the ST end of the curve, for positive and negative exposures respectively. Here the 10-day FHS model achieves 58.17% for the decreasing LO profile and only 30.86% for the increasing SO profile at the 99% level. The SIMM gives 71.32% for this type of profile, still higher than both the 10-day estimates. Here the skew is more pronounced than the previous case, since the volatilities and skews for the ST tenors are more pronounced in the historical sample.

Table 4.10: **Linear**: IM as a percentage of absolute PV01 exposure for the linear increasing and decreasing profiles (3.3). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO, SO and LS variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	Increasing	26.04	38.30	48.13	31.23	46.99	57.65	40.00	63.57	74.77	89.28	83.17
	Decreasing	29.45	40.80	48.64	44.74	58.17	65.94	66.93	88.96	101.18	70.16	71.32
SO	Increasing	17.37	23.34	29.84	23.34	30.86	40.49	33.94	44.18	62.89	70.16	71.32
	Decreasing	30.16	44.19	58.29	39.04	58.37	78.27	57.02	89.29	117.71	89.28	83.17
L-S	Increasing	16.63	23.76	29.78	21.06	29.16	36.23	30.18	39.08	49.17	52.58	52.91
	Decreasing	25.25	35.16	43.22	34.74	47.66	57.39	50.34	73.98	86.41	52.58	52.91

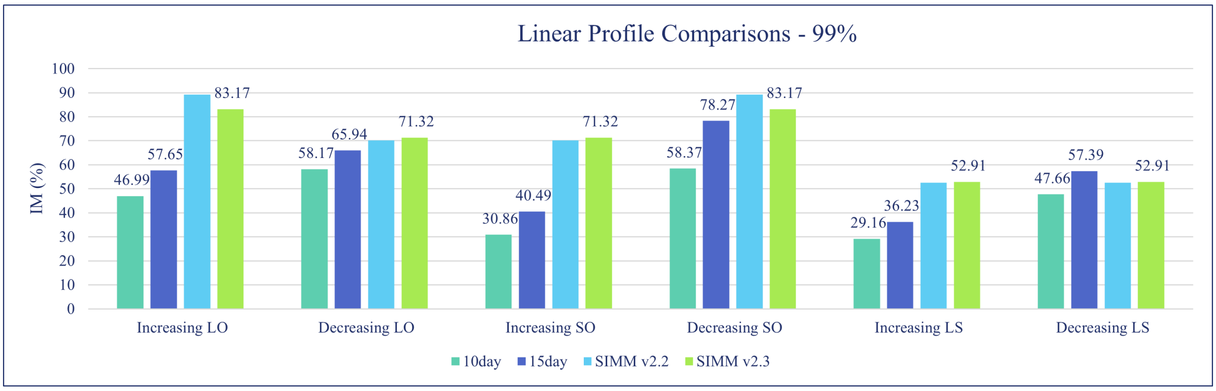


Figure 4.12: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **linear** profiles.

The pronounced skews have a considerable effect on the LS portfolios in this comparison, where both long and short exposures are considered. The increasing LS profile has negative PV01 exposures up until the 2Y rate, and positive exposures from the 3Y to 30Y that increase in a linear fashion. The decreasing profile has the same shape but the negative of this PV01 profile, i.e. positive short end exposures and negative long end. As expected from the ST vs LT comparisons, these portfolios accentuate the skews of the ST and LT tenors. The decreasing LS has the most pronounced effect, which gives positive weights to the ST exposures that have more tail risk than the short exposures, and short positions in LT tenors, which have more tail risk than the long exposures. The results at the 99% level are 47.66% for the h-day simulation and 57.39% for the 15-day simulation. The SIMM is 52.91%, and therefore the 15-day estimate is higher, as a result of exploiting the asymmetry of the simulated distributions. The SIMM is still adequate under the required 10-day 99% calibration.

Sine and Cosine Profiles

The results for the sine and cosine type distributions show how the IM results behave for the different models for varying exposure shapes. The sine increasing LO and sine decreasing SO results are comparable in table 4.11 and figure 4.13. These profiles place their greatest weight, in terms of magnitude, at the 6M tenor and the minimum at the 10Y tenor, in table 3.4. Here there is a significant difference once again between the LO and SO values at the 99% level for the FHS model. This is consistent, however, with the results found so far.

Comparable with these sine results in particular are the cosine decreasing LO and cosine increasing SO results in table 4.12 and figure 4.14. These profiles place their maximal weights, with regard to magnitude, at the 2W and 30Y tenor and minimal weights at the 2Y and 3Y tenors. Therefore the SIMM values are not the same, with 70.8% for the sine profiles and 69.30% for the cosine profiles, regarding SIMM version 2.3, but the results are very close. Here the FHS ES results of 50.53% for the cosine decreasing LO profile and 37.84% for cosine increasing SO portfolio are quite similar compared to the results for the sine profiles, sine increasing LO (52.59%) and sine decreasing SO (31.76%). Note that the sine value is larger in the former case, and in contrast to the SIMM the cosine estimate is larger in the latter comparison.

Now consider the sine decreasing LO and sine increasing SO profiles, which can also be compared to the cosine increasing LO and cosine decreasing SO results. Here the maximal and minimal weights

Table 4.11: **Sine**: IM as a percentage of absolute PV01 exposure for the sine increasing and decreasing profiles (3.4). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO, SO and LS variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	Increasing	27.12	37.43	44.18	40.98	52.59	60.21	61.27	83.63	94.56	71.56	70.98
	Decreasing	25.45	37.51	47.02	30.38	45.96	56.33	38.37	62.94	73.07	85.93	80.84
SO	Increasing	28.92	42.48	56.08	37.23	55.81	75.45	53.75	84.46	112.89	85.93	80.84
	Decreasing	17.06	23.68	30.78	23.28	31.76	42.43	35.74	47.42	66.17	71.56	70.98
L-S	Increasing	18.70	26.25	32.70	25.17	35.78	44.21	37.02	58.33	71.18	43.24	42.86
	Decreasing	13.11	18.66	23.82	16.26	22.71	29.26	22.06	30.61	40.95	43.24	42.86

Table 4.12: **Cosine**: IM as a percentage of absolute PV01 exposure for the cosine increasing and decreasing profiles (3.5). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO, SO and LS variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	Decreasing	26.22	36.99	44.71	37.98	50.53	58.73	57.32	75.68	87.19	66.68	69.30
	Increasing	24.20	35.45	43.69	30.89	45.88	54.51	44.84	68.58	76.54	88.55	78.65
SO	Decreasing	25.40	36.57	48.15	33.53	48.66	66.37	50.32	76.22	99.04	88.55	78.65
	Increasing	20.19	29.33	38.62	26.21	37.84	51.72	37.67	56.74	78.02	66.68	69.30
L-S	Decreasing	13.06	17.92	21.99	19.56	26.07	30.49	30.30	41.04	46.26	24.96	23.53
	Increasing	9.23	12.31	15.44	12.53	15.92	19.97	18.07	23.06	30.03	24.96	23.53

are reversed, so they stress the same tenors, but at the opposite ends of the trade. The SIMM obtains 80.84% for the sine profiles and 78.65% for the cosine profiles. The sine decreasing LO and the cosine increasing LO obtain similar 10-day 99% FHS ES estimates of 45.96% and 45.88%. The cosine decreasing SO value is not that much different at 48.66%, showing more symmetry than the sine profile, since the sine increasing SO value is much higher at 55.81%. Looking back at figure 4.1, one can see that the 2Y and 3Y tenors obtain more symmetrical results, which explains why the cosine obtains more symmetrical results here.

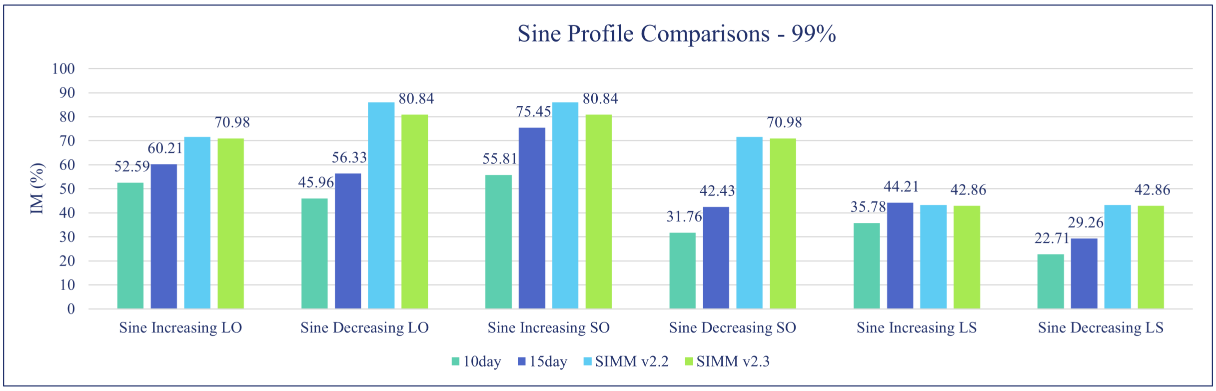


Figure 4.13: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **sine** profiles.

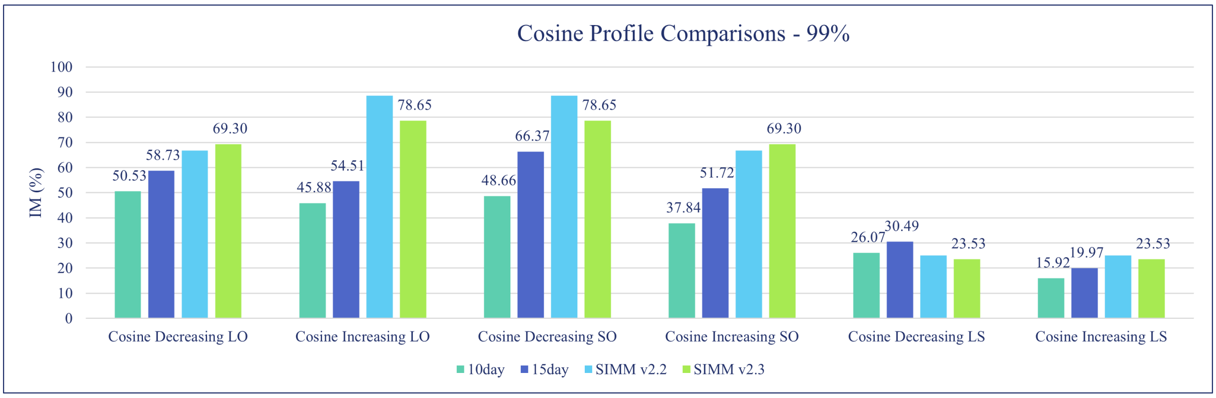


Figure 4.14: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **cosine** profiles.

The LS profiles for the sine and cosine shapes will show how the SIMM correlations perform when positive and negative exposures are considered for profiles with these shapes. The sine increasing LS, gives maximal positive weight at the 6M tenor and maximal negative weight at the 10Y tenor, thus investigating the cancellation effects of these tenors to an extent. The sine decreasing LS profile is simply the negative of this profile, and its results show the opposite end of the return distribution. The SIMM here obtains 42.86% compared to 35.75% and 22.71% 10-day 99% ES estimates for the increasing and decreasing profiles. The increasing profile shows the same accentuation of the skew effect that can be seen in the ST vs LT and linear LS comparisons.

The cosine decreasing LS portfolio places maximal positive weight at the 2W and 30Y tenors and maximal negative weights at the 2Y and 3Y tenor. This profile in particular places relatively large positive weight at the 2W rate, which shows to be the riskiest rates for the long side in the current market. This finding in conjunction with the low correlations of this rate with the 2Y and 3Y tenors, in table 4.9, result in a 10-day 99% estimate of 26.07% that breaches the SIMM value of 23.53%. Particular attention should be paid to the shape of this profile (table 3.5 and figure 3.4), as it is the first type of portfolio that is seen to lead to a breach of the SIMM at the relevant risk calibration.

The cosine increasing LS is the negative of the cosine decreasing LS profile and shows smaller estimates of 15.92% for the 10-day 99% ES value in comparison. Both the LS cosine estimates are lower than the sine estimates when looking at the SIMM and the same trend is present in the FHS estimates. When comparing the FHS 10-day 99% estimates results to their respective SIMMs, the cosine FHS estimates are relatively higher than the sine estimates. This indicates that the cosine profiles, and the cosine decreasing LS profile in particular, show some uncovered risk exposure.

Exponential Profiles

The penultimate analysis is using exponential profiles. In this case only LO and SO profiles are considered where the increasing LO and decreasing SO are comparable, and the decreasing LO and increasing SO are comparable. From figure 4.15, one can see a large value obtained for the 10-day 99% estimate of 82.58% for the decreasing LO profile, which is higher than the SIMM value of 77.8%. Looking at the shape of this profile in table 3.6, one can see that it heavily weights the 2W tenor, which has shown to be the cause of most of the exceedances of SIMM so far. This profile puts heavier weight on the 2W rate relative to the other rates compared to the linear profiles, thus pronouncing the skew significantly more. The increasing SO, in comparison, achieves a 34.17% estimate, which means the LO exposure is approximately 2.42 times larger than the SO exposure. This is consistent with the difference in distributions for the isolated 2W rate in section 4.2, where the LO is larger than the SO estimate by a factor of 2.07.

Table 4.13: **Exponential**: IM as a percentage of absolute PV01 exposure for the exponential increasing and decreasing profiles (3.6). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO and SO variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	Increasing	28.68	42.21	53.50	33.82	50.95	63.91	41.37	67.67	81.91	94.71	90.59
	Decreasing	40.82	56.37	67.41	63.02	82.58	94.03	96.99	127.57	142.79	68.78	77.80
SO	Increasing	20.97	27.33	31.24	29.22	34.17	40.08	38.85	43.82	60.09	68.78	77.80
	Decreasing	34.14	50.39	66.32	43.75	66.30	88.41	62.90	100.94	132.11	94.71	90.59

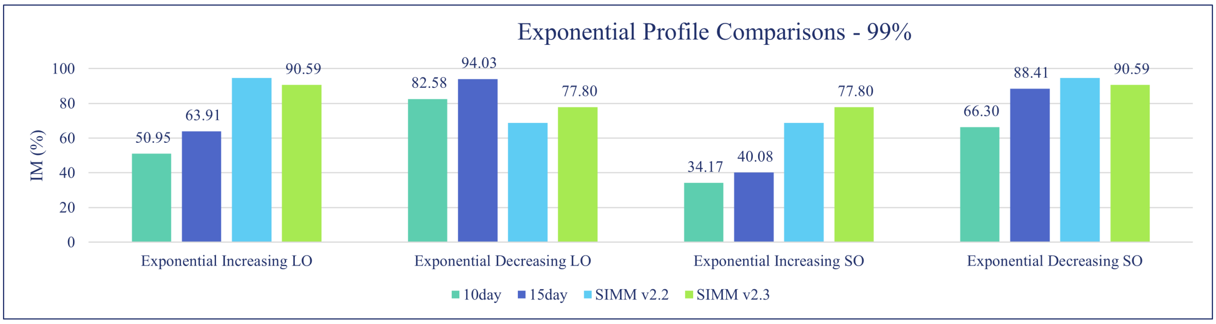


Figure 4.15: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **exponential** profiles.

Alternating Profiles

Lastly the alternating comparisons are made. Figure 4.16 summarises the 99% level findings of the results in table 4.14. Comparing first the LO results, one can see that the results are similar for the two profiles. The two profiles give approximately the same wight to each end of the curve, with a focus on a different tenor. Therefore the results here are similar to the flat comparisons made earlier in the section.

Note that the SIMM version 2.3 estimate for profile 2 (73.09%) is larger than the SIMM estimate for profile 1 (71.68%) for the LO and SO comparisons. The FHS LO estimates, in contrast, show the profile 1 estimate (45.46%) to be larger than profile 2 (44.27%). The SO comparisons follow the same trend as SIMM and show the profile 2 estimates (44.80%) to be larger than the profile 1 estimate (39.90%) at the 10-day 99% level.

Table 4.14: **Alternating**: IM as a percentage of absolute PV01 exposure for the alternating profiles (3.7). The ES estimates of the h-day FHS models are given at various levels of α. The SIMM IM estimates for version 2.2 and 2.3 are presented alongside the FHS results for the LO, SO and LS variations. Primary comparison should be made with the SIMM values and the 99% 10-day estimates.

	α	97.50%			99.00%			99.75%			SIMM	
Type	h	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
LO	Profile 1	24.49	34.88	41.81	33.29	45.46	53.00	47.97	64.98	76.39	73.46	71.68
	Profile 2	23.67	34.21	41.64	30.93	44.27	52.79	44.84	66.82	76.94	77.31	73.09
SO	Profile 1	21.52	30.47	40.00	28.04	39.90	54.15	40.59	60.93	79.80	73.46	71.68
	Profile 2	23.12	33.77	44.93	30.24	44.80	61.12	45.01	70.34	93.08	77.31	73.09
L-S	Profile 1	4.09	5.74	7.60	5.60	7.72	10.30	8.95	11.10	15.44	7.93	8.43
	Profile 2	3.94	5.52	6.28	5.26	7.08	7.79	7.62	9.38	10.28	7.93	8.43

Profile 1 LO and profile 1 SO are comparable, and similarly profile 2 LO and profile 2 SO are comparable. Here one can see that the profile 2 results in a more symmetric distribution than profile 1. This is perhaps due to the zero weight given to the 2W tenor in profile 2, which is the rate that tends to inflate the differences in the two tails. Here profile 2 SO (48.80%) also produces a slightly higher estimate than profile 2 LO (44.27%), in contrast to the results of profile 1 at the 10-day 99% level. Interestingly the SO FHS estimate show higher results for both profiles at the 15-day calibration. These estimates are still below the SIMM estimates, which only the 15-day 99.75% estimates seem to surpass.

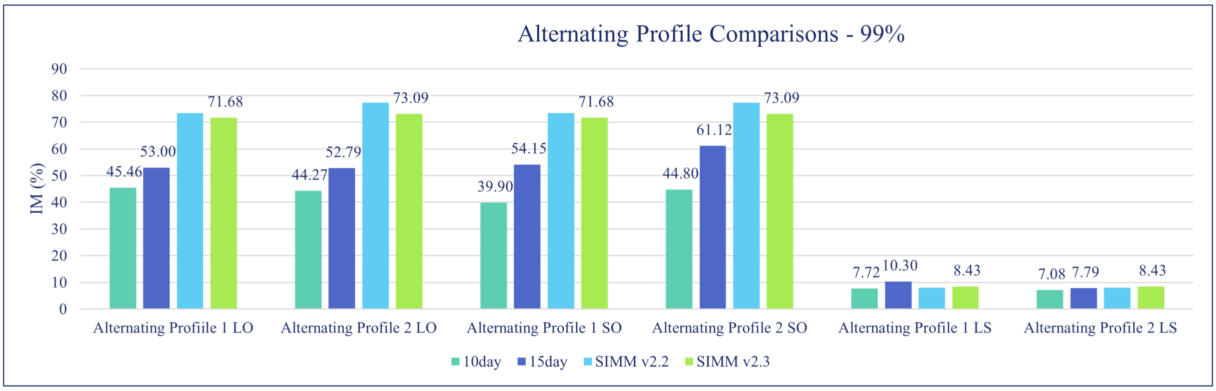


Figure 4.16: A bar plot showing the 10-day and 15-day FHS ES estimates at the 99% level compared to SIMM versions 2.2 and 2.3 for the **alternating** profiles.

Considering the LS comparison, it is clear that these result in the highest diversification benefit than all other comparison made so far. This is because the rates at the ends of the curve are highly correlated to one another and therefore cancel out to an extent in the SIMM and FHS models. Here the SIMM obtains an IM estimate of only 8.43%, while profile 1 achieves 7.72% and profile 2 achieves 7.08%. For such a profile the risk is much lower, and thus a lower IM is required as a percentage of absolute exposure is much lower.

It is interesting to see that the 15-day estimate for profile 1 LS is much higher (relative terms) than for profile 2 LS, whereas the 15-day estimate of for profile 2 SO is the highest 15-day estimate achieved at 61.12%. This phenomena may be for the same reasons, as the profile 1 LS may have negative weights at the same tenors that cause profile 2 SO's 15-day estimate to be so high.

Preliminary Findings

The results here have shown the 2W tenor to have a considerable influence on the IM estimates in the CCP model. The skewness in the distributions found in the results in section 4.2 have persisted in this section. By looking at the estimated correlation structure of the simulated distributions and comparing them to the SIMM weights, one finds reasonable explanations for why the SIMM and FHS models follow different trends, although the SIMM is sufficient to cover the risks at the 10-day 99% risk level for many of the profiles. The profiles that have resulted in 10-day 99% estimates that are larger than the SIMM are the cosine decreasing LS and exponential decreasing LO profiles.

It is shown here how the IM requirements are different depending on which side of the trade one is on for the CCP model, for standardised shapes and profiles. Now that an understanding of how the shapes influence the IM estimates for the two models, one can start to stress the models in a way that further informs one of the risks involved. The next section aims to find the profiles that show high model risk, and with the knowledge provided in this section, the reasons for the results found can be elucidated.

4.4 RESULTS OF RANDOMISED PORTFOLIO COMPARISONS

The results of the randomised comparison analysis is discussed in this section whe the results are summarised in tables 4.15 to 4.17. The average result of the estimates from the simulations, for each risk calibration and SIMM, is given in each table. Each table also contains the IM (as a percentage of PV01 exposure) for the portfolio that results in the smallest SIMM estimate, the largest SIMM estimate and the largest FHS for estimates at the 10-day 99% risk calibration. It also contains either the portfolio that results in the largest relative difference or absolute difference between the two models at the 10-day 99% level. This section analysis and discusses these results, where figures are given to summarise the findings. Figures are also given to display the PV01 exposures for the portfolios of interest. The index column in the tables refers to the number of the simulated distribution that gave the key result. The index is used to retrieve the shape of the profile that created the results so that it can be inspected.

Table 4.15: Results for the randomised LO comparisons. Shown are the average values obtained under both models. The FHS ES shortfall is given for various specifications of α and h and compared to the results of SIMM versions 2.2 and 2.3. The index is given of the portfolio that resulted in either the smallest SIMM, the largest SIMM, the largest FHS or the largest absolute difference. The averages of the results for all of the portfolios in the LO analysis is also presented for both models.

	α	97.50%			99.00%			99.75%			SIMM	
	Index	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
Average		23.16	31.21	39.99	31.34	39.41	51.32	48.03	53.98	76.10	76.05	73.06
Smallest SIMM	845	25.27	32.28	41.36	39.08	44.37	57.66	66.49	64.33	96.59	67.42	68.29
Largest SIMM	815	25.70	37.60	48.15	30.32	44.36	57.30	36.56	56.18	73.13	91.27	86.23
Largest FHS	575	32.84	43.29	53.67	52.86	60.84	75.34	88.65	86.16	121.33	64.35	71.77
Largest Difference	666	25.10	37.15	47.42	29.74	43.82	56.25	35.81	56.06	70.96	91.35	85.95

Table 4.16: Results for the randomised SO comparisons. Shown are the average values obtained under both models. The FHS ES shortfall is given for various specifications of α and h and compared to the results of SIMM versions 2.2 and 2.3. The index is given of the portfolio that resulted in either the smallest SIMM, the largest SIMM, the largest FHS or the largest absolute difference. The averages of the results for all of the portfolios in the SO analysis is also presented for both models.

	α	97.50%			99.00%			99.75%			SIMM	
	Index	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
Average		21.16	31.20	38.05	28.34	42.10	50.35	44.76	64.49	76.65	76.02	73.10
Smallest SIMM	244	18.84	27.64	33.58	25.35	37.10	44.26	39.28	55.95	65.25	67.86	68.19
Largest SIMM	694	29.60	43.82	54.46	39.02	57.68	70.73	60.01	85.27	104.37	90.88	85.33
Largest FHS	694	29.60	43.82	54.46	39.02	57.68	70.73	60.01	85.27	104.37	90.88	85.33
Largest Difference	408	16.77	23.64	27.51	22.80	32.05	37.15	34.68	50.85	57.23	68.84	71.99

Table 4.17: Results for the randomised portfolio comparisons, that have both positive and negative PV01 exposures. The FHS ES shortfall is given for various specifications of α and h and compared to the results of SIMM versions 2.2 and 2.3. The index is given of the portfolio that resulted in either the smallest SIMM, the largest SIMM, the largest FHS or the largest relative difference. The averages of the results for all of the portfolios in this analysis is also presented for both models.

	α	97.50%			99.00%			99.75%			SIMM	
	Index	5day	10day	15day	5day	10day	15day	5day	10day	15day	v2.2	v2.3
Average		10.51	14.75	18.45	14.56	19.53	24.47	22.89	28.85	37.73	31.44	30.94
Smallest SIMM	205	3.51	5.66	7.02	4.65	7.63	9.21	7.09	11.45	13.79	8.48	8.05
Largest SIMM	943	22.18	30.36	38.63	28.36	37.43	48.28	40.73	49.71	66.65	79.89	74.28
Largest FHS	709	21.58	31.58	38.34	29.04	42.85	51.21	46.55	66.81	80.59	69.11	62.37
Largest Difference*	239	10.30	13.52	16.77	17.28	19.57	23.68	28.94	28.87	40.28	12.05	13.93

* Largest relative difference obtained by taking the largest ratio of the FHS ES 10-day 99% estimate and the SIMM version 2.3 estimate.

Average Comparisons

Continuing the investigation into the difference in the tail risks presented by the FHS model, the average values[1] in tables 4.15 to 4.17 allow for a general comparison into relevant risk coverage of SIMM with regard to the two sides of a swap trade. Starting with a look at the SIMM version 2.3 value of 73.06%, in table 4.15 which contains the results for portfolios with only positive PV01 values and comparing it to SIMM version 2.3 average IM estimate of 73.10%, in table 4.16, one can see that there is virtually no difference between the simulated portfolios on average for the two sides. It is expected that these two results would be very similar by nature of the design of the experiment.

Looking at the average 10-day 99% IM values of the two tables, notice that the 39.41% of table 4.15 and the 42.10% estimate of table 4.16 are very similar, but not as close as the SIMM estimates are to one another. One can conclude that at this quantile the two sides of the distribution are very similar. The symmetry here is perhaps the same feature that was seen in the flat comparisons from section 4.3, where the skew on the short end and skew on the long end cancel each other out when taking averages.

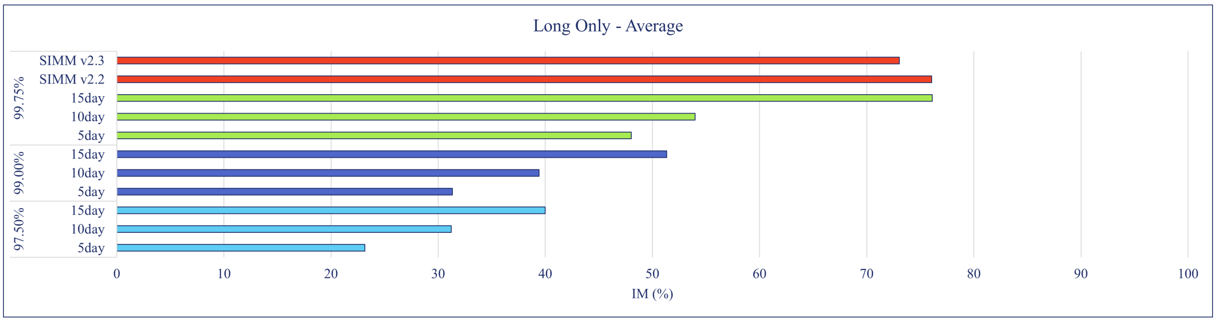


Figure 4.17: Horizontal bar plot showing the average results of the LO randomised portfolio comparisons.

The IM estimates for randomised portfolios, containing both positive and negative PV01 exposures, in table 4.16 can be compared to the LO and SO results as well. Firstly, SIMM version 2.3 gives an IM estimate of 30.94% which is less than half the estimate for the LO and SO profiles. This is expected since the inclusion of positive and negative exposures creates significant diversification

[1]These are simply the equally weighted average results of the 1000 IM results for each of the model calibrations in the three main analyses in this section.

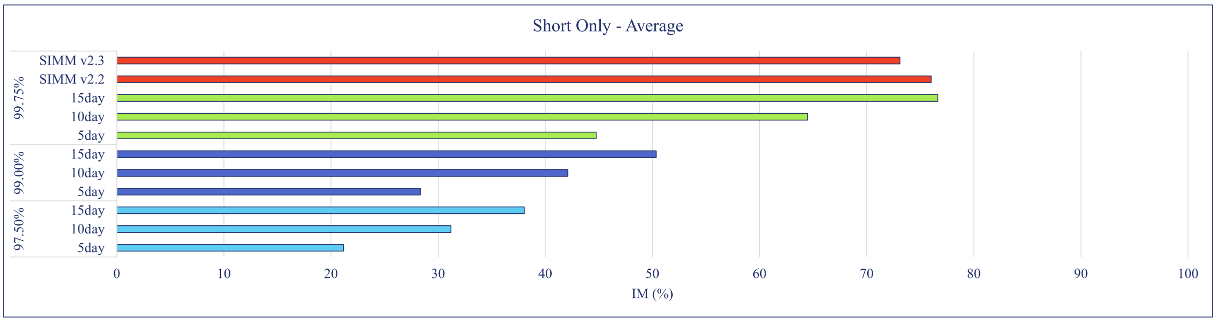


Figure 4.18: Horizontal bar plot showing the average results of the SO randomised portfolio comparisons.

benefit in both models. The 10-day 99% IM estimate from the FHS ES model gives 19.53% on average which is approximately half the LO and SO estimates. Therefore the FHS model does not give as generous a diversification benefit as the SIMM, which was already evident in section 4.3 when looking at the LS profiles that lead to relative exceedances.

The FHS model is able to capture the correlations between the rates at the extreme quantiles of the portfolio distributions better than the SIMM model, which has a much more rigid correlation calibration. When positive and negative PV01 exposure are present in a portfolio, the SIMM has the danger of over-estimating the cancellation effects of tenors, by assuming high correlations when lower correlations may be more appropriate with regard to the extreme movements of certain semi-diversified portfolios. Therefore in figure 4.19 the IM requirements are greater in relation to SIMM for all the risk calibrations than in figures 4.17 and 4.18.

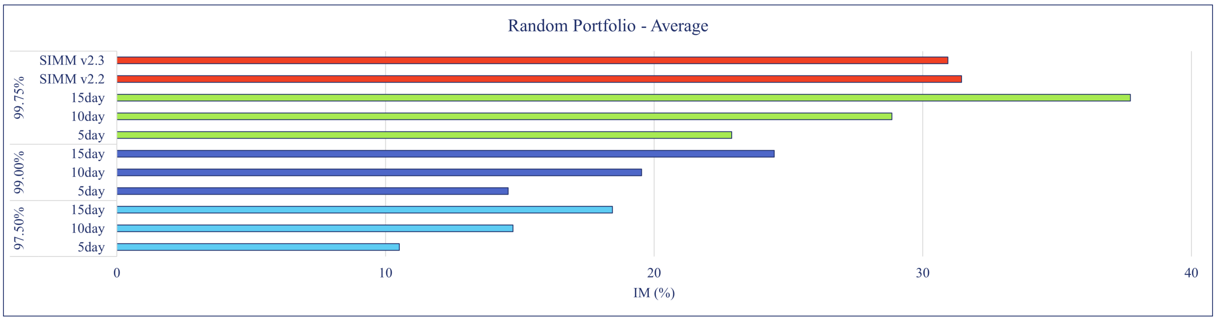


Figure 4.19: Horizontal bar plot showing the average results of the randomised (LS) portfolio comparisons.

LO Profile Comparisons

Figures 4.20 to 4.24 aim to visualise the results for the key LO portfolios in table 4.15. The portfolios themselves that create these results can be seen in the corresponding figures 4.21a to 4.21d. The smallest SIMM refers to the LO portfolio that generated the smallest IM as a percentage of the absolute portfolio PV01 exposure in absolute terms. The smallest SIMM value obtained is 68.29% and the corresponding 10-day 99% FHS ES estimate is also relatively low at 44.37%. The portfolio that generated this estimate, given in figure 4.21a, put its greatest weights on the 3M and 20Y tenor. When compared to the cosine decreasing LO profile (results given in table 4.12) which also obtained a close 69.30% SIMM estimate, but a relatively higher FHS estimate (50.53%) is obtained in that case due to the long-side tail risk of the 2W tenor. Only the 10-day and 15-day FHS estimate at the 99.75% level breaches the SIMM estimates for this profile which is also the case for the cosine decreasing LO profile.

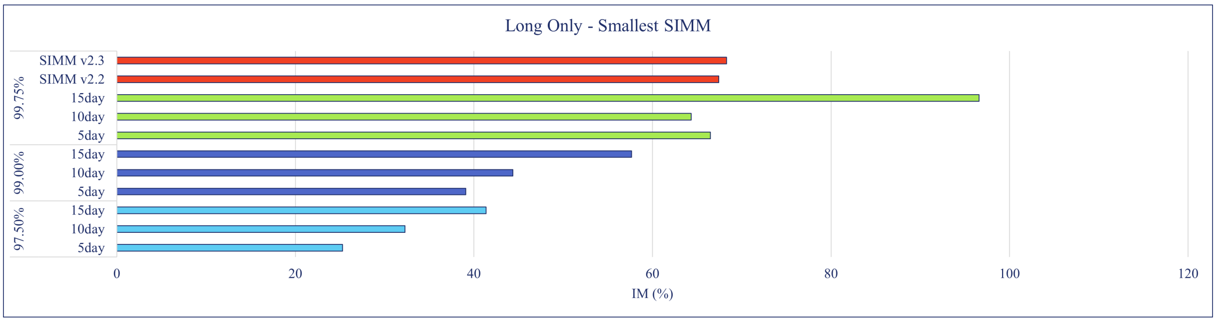
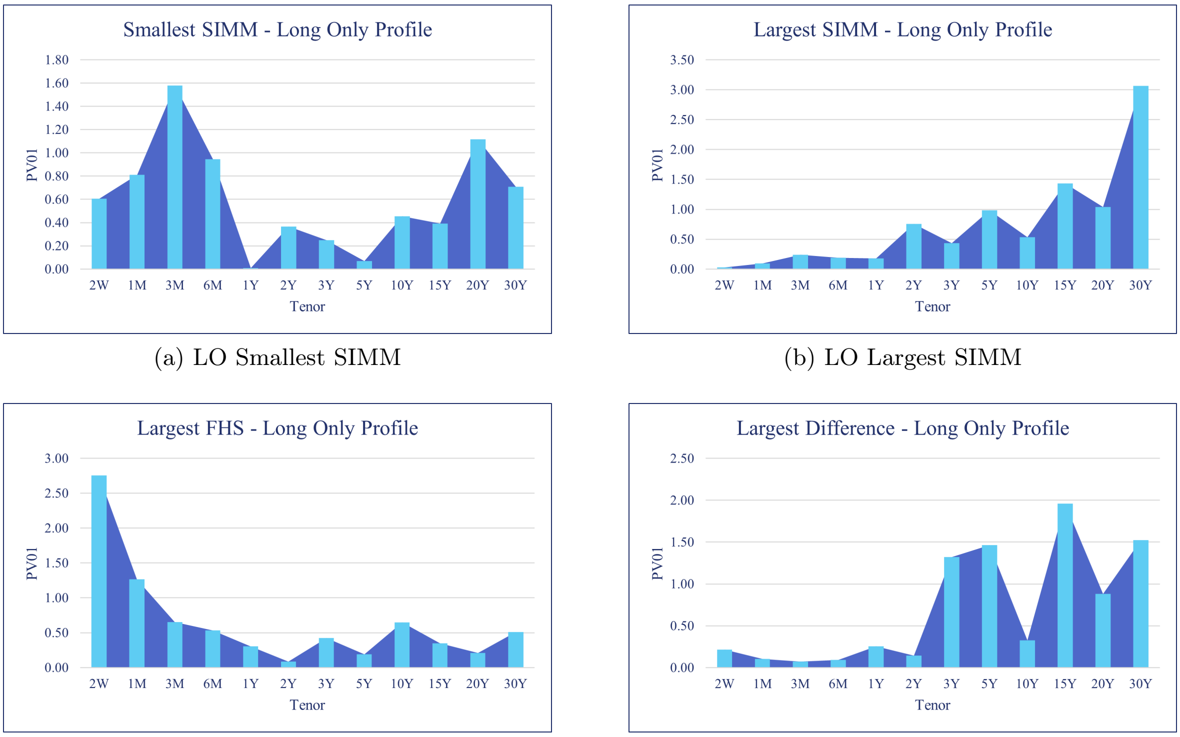


Figure 4.20: Horizontal bar plot showing the results of the portfolio, from the LO randomised comparisons, that obtained the **smallest SIMM** version 2.3 estimate.

Figure 4.22 shows the IM estimates for the portfolio that generated the largest SIMM version 2.3 estimate out of all the randomised LO portfolios in this analysis. In fact, this portfolio (LO index 815) generated the highest SIMM estimate for all the randomised portfolios in this section with 86.23%. The largest SIMM estimate out of all the portfolio comparisons so far is the 90.59% estimate for the exponential increasing LO (or decreasing SO) profile, which is very similar in shape to the PV01 profile in figure 4.22. In this case the heaviest weight is given to the 30Y tenor and the next heaviest weights are given to the 15Y and 20Y tenor, which have a very high correlation with the 30Y tenor in the SIMM model. The 10-day 99% estimate is 44.36% for comparison which is about the same as the FHS estimate (44.37%) obtained for the smallest SIMM portfolio.



(a) LO Smallest SIMM

(b) LO Largest SIMM

(c) LO Largest FHS

(d) LO Largest Difference

Figure 4.21: The key LO randomised profiles. These profiles correspond to the key results in table 4.15.

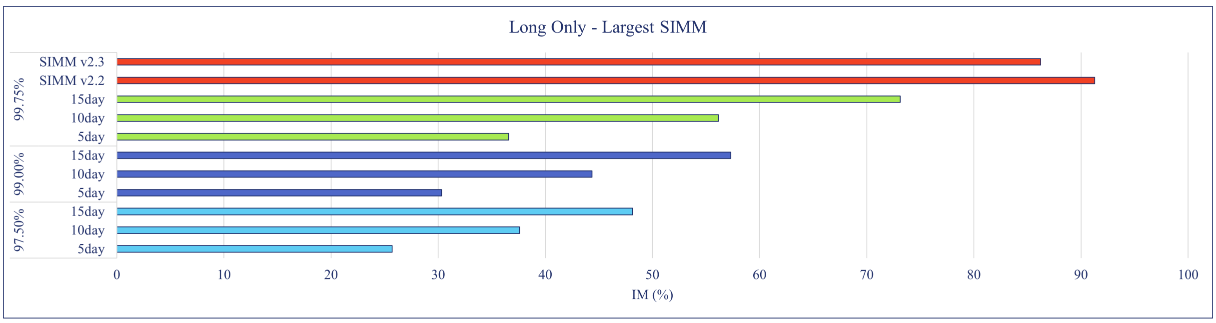


Figure 4.22: Horizontal bar plot showing the results of the portfolio, from the LO randomised comparisons, that obtained the **largest SIMM** version 2.3 estimate.

This feature, and discoveries from prior analysis, allude to the prospect that SIMM and FHS models imply different profile types for what they deem the riskiest LO portfolio to be. The profile that obtained the largest absolute FHS estimate in the LO analysis, in figure 4.23, has the opposite exponential shape compared to the profile that produced the largest SIMM estimate. For this portfolio the 10-day 99% FHS estimate is 60.84%, the closest estimate relative to its SIMM version 2.3 estimate of 71.77% in the LO analysis. Here the 15-day 99% as well as the 5-day, 10-day and 15-day 99.75% IM estimate breach the value of SIMM. This comparison confirms in essence that the models have different definitions of what they deem to be most risky in the LO case.

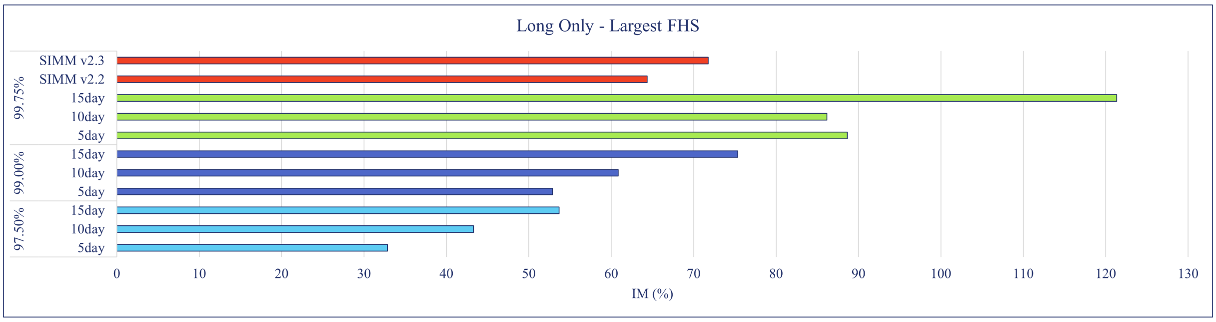


Figure 4.23: Horizontal bar plot showing the results of the portfolio, from the LO randomised comparisons, that obtained the **largest FHS** ES estimate at the 10-day 99% calibration.

The portfolio that leads to the largest relative difference between the two models is the one leading to the largest FHS in this case. To stress the idea that the models have inherently different risk definitions it would be relevant to look at the profile that leads to the largest absolute difference in estimates. This profile is given in figure 4.21d, and shows relatively small weights at the short end of the curve and heavier weights at the LT tenors, signature of what one can expect from the largest SIMM LO profile comparison. Here the SIMM is 85.95% and the FHS estimate 43.82%, showing a difference of 42.13% in absolute terms. Hence although the SIMM is adequate to cover this risk, the coverage is not uniform, since the FHS model essentially implies different risk weights and correlations to the SIMM.

SO Profile Comparisons

It is not surprising that the key SIMM profiles for the SO (figure 4.25) and LO (4.21) randomised comparisons are so similar, after all the SIMM is a symmetrical model. The SO profiles, however, show different results for the largest FHS compared to the estimates for the LO profiles discussed

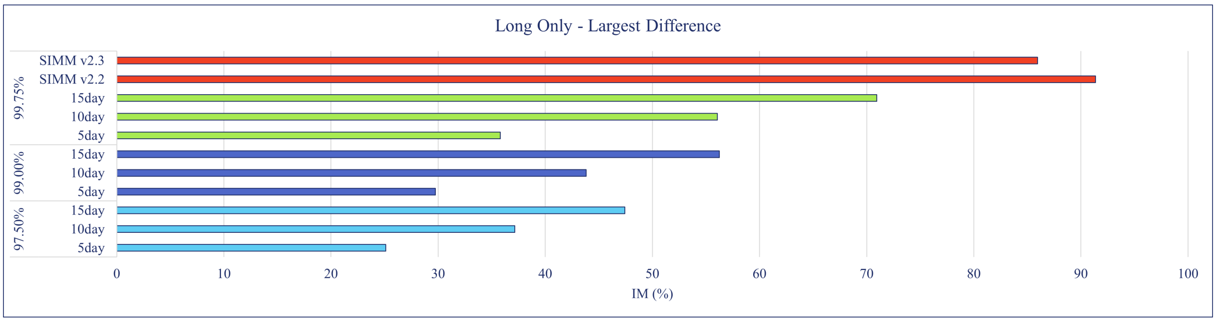
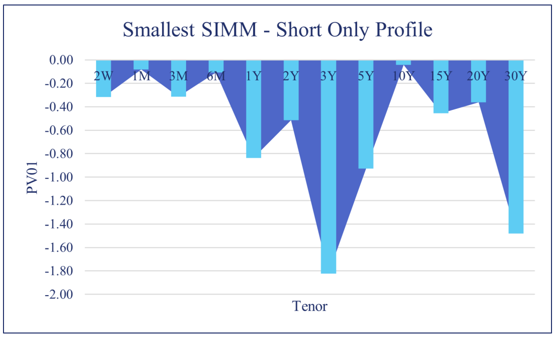
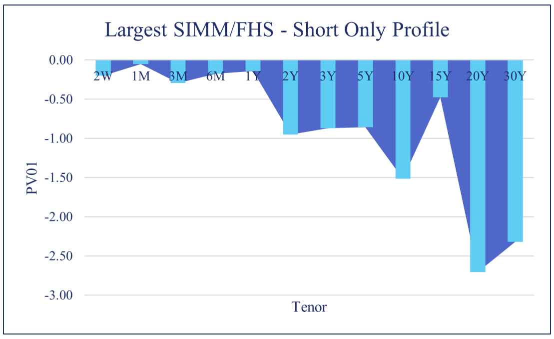


Figure 4.24: Horizontal bar plot showing the results of the portfolio, from the LO randomised comparisons, that obtained the **largest absolute difference** between the ES estimate at the 10-day 99% calibration and the SIMM version 2.3 estimate.

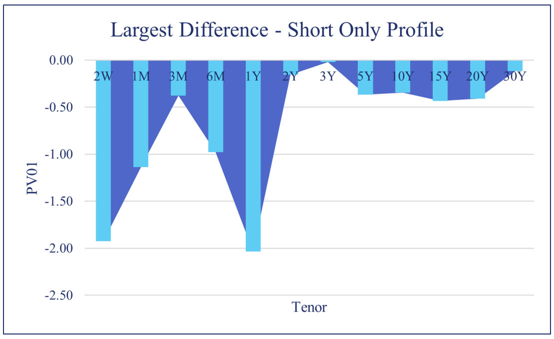
above, which is expected due to the findings in sections 4.2 and 4.3 which show the LO and SO risks to behave differently depending on the maturities of the exposures.



(a) SO Smallest SIMM



(b) SO Largest SIMM and FHS



(c) SO Largest Difference

Figure 4.25: The key SO randomised profiles. These profiles correspond to the key results in table 4.16.

Both the smallest SIMM profile in figure 4.25a and the SIMM estimate of 68.19% in table 4.16 are very similar to the LO result (68.29%) and profile, in figure 4.21a, although these are not exactly the same. This difference is due to different random portfolios being generated in the two comparisons, otherwise the results and profile would match exactly. Because of the symmetry of SIMM, the profile resulting in the largest SIMM estimate in figure 4.27 is similar to the exponential shape seen in figure 4.21b for the LO case. The FHS estimate for the smallest SIMM profile is relatively smaller in the SO case compared to the LO case with 37.10% compared to 44.37% (10-day 99%) and does not surpass SIMM at any of the risk settings, seen in figure 4.26.

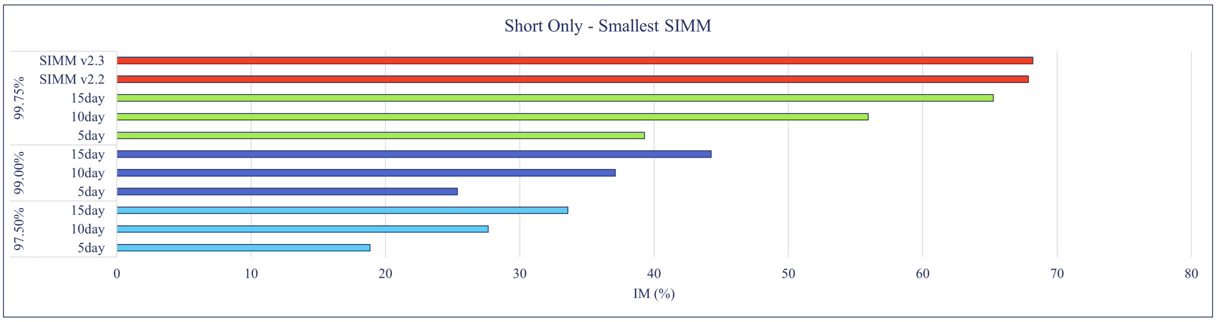


Figure 4.26: Horizontal bar plot showing the results of the portfolio, from the SO randomised comparisons, that obtained the **smallest SIMM** version 2.3 estimate.

The opposite can be seen when considering the profile that leads to the largest SIMM estimate, where the 57.68% SO estimate trumps the 44.36% estimate for the LO case. In fact, for the SO case it is the same portfolio that produces the largest SIMM and largest FHS estimates. This is in concordance with the findings from before, where the FHS model produces larger estimates on the SO side for the longer tenors compared to shorter tenors. This shows exactly the opposite trend that the LO exposures show under the FHS model. Thus the SO FHS estimates and SIMM have a definition of the riskiest portfolio that is more aligned than what appears to be the case when comparing SIMM and the LO estimates. Hence the FHS estimate only achieves a higher IM estimate at the 15-day 99.75% calibration in figure 4.27 and is the closest the FHS gets to SIMM at the 10-day 99% level in relative terms out of all the profiles considered in the SO analysis.

The opposite behaviour of the LO and SO results for these comparisons is seen again when comparing figures 4.21d and 4.25c. The profiles that result in the absolute largest difference between the FHS estimates shows results consistent with the LT vs ST comparisons made in section 4.3, which showed the ST SO to be the smaller SO estimate and LT LO to have the lowest LO estimate. The SO largest difference profile, in this case, puts heavy weights on the ST tenors whereas the LO profile

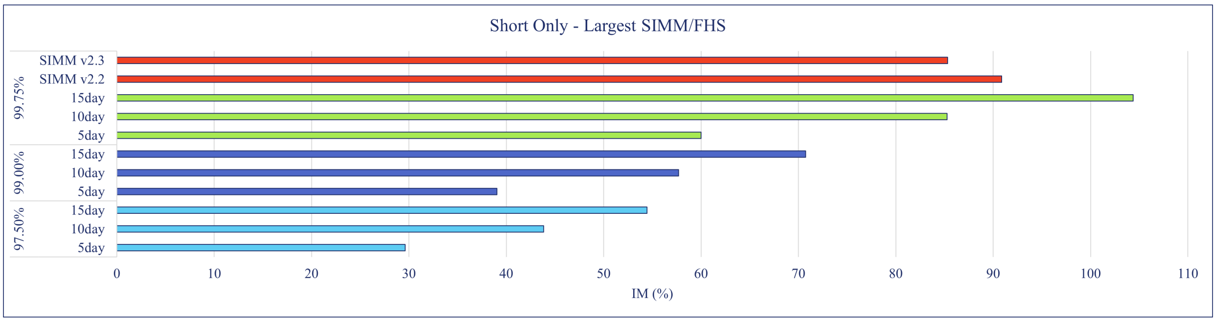


Figure 4.27: Horizontal bar plot showing the results of the portfolio, from the SO randomised comparisons, that obtained the **largest SIMM** version 2.3 estimate and the **largest FHS** ES estimate at the 10-day 99% calibration.

that results in the largest absolute difference puts its weights on the LT tenors. Therefore, along with the findings of before, the LO side is riskier for short maturities whereas the SO side is riskier for longer maturities.

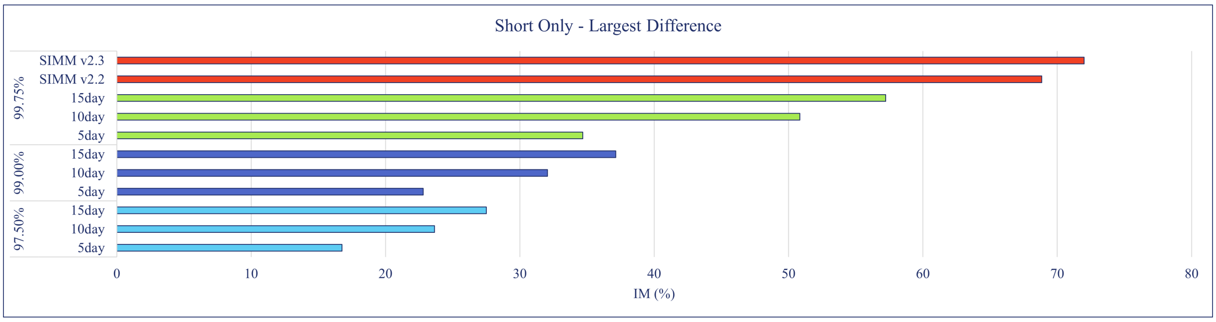
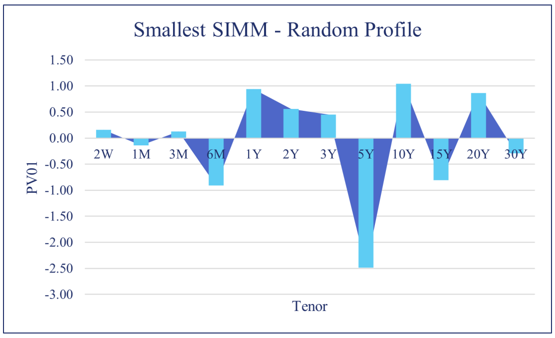


Figure 4.28: Horizontal bar plot showing the results of the portfolio, from the SO randomised comparisons, that obtained the **largest absolute difference** between the ES estimate at the 10-day 99% calibration and the SIMM version 2.3 estimate.

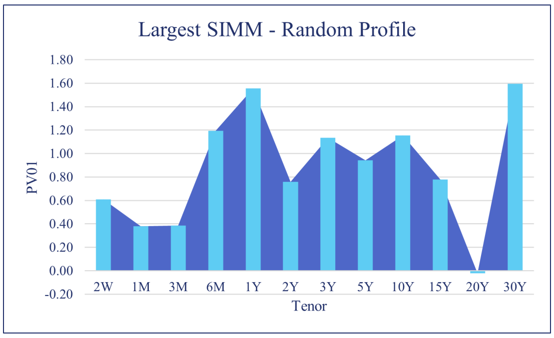
Long-Short Profile Comparisons

It is clear that there is a difference in the LO and SO tail risks that present themselves. This difference has not yet appeared to be a cause of major concern as the SIMM is sufficient to cover the 10-day 99% risk threshold in all cases so far. Where this apparent asymmetry may present itself as a real weakness for SIMM may become evident when looking at the results obtained for the LS comparisons of table 4.17.

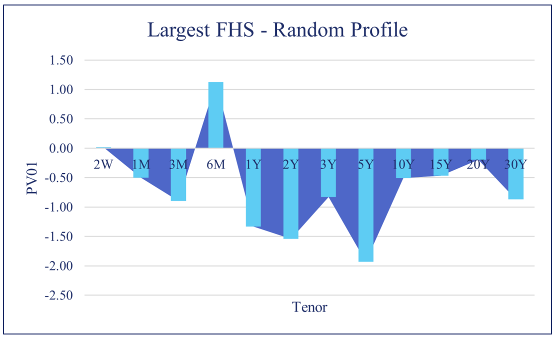
The smallest SIMM estimate obtained is 8.05%, which is even smaller than the alternating LS profile results in table 3.7 of 8.43%, the smallest result of the comparisons in section 4.3. This profile in figure 4.29a does not have a strictly alternating shape as before, but it has that appearance. Figure 4.30 shows how the 15-day 99% estimate, and the 10-day and 15-day 99.75% estimates are larger than the SIMM. The 10-day 99% FHS ES estimate is still below the SIMM with 7.63%.



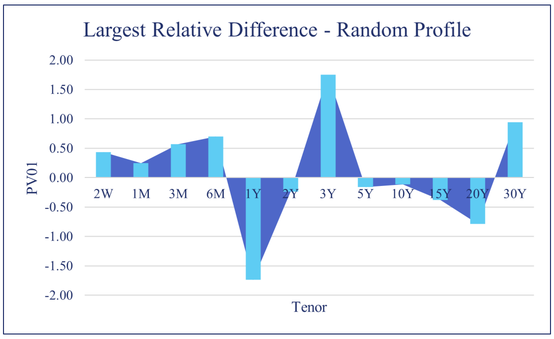
(a) LS Smallest SIMM



(b) LS Largest SIMM



(c) LS Largest FHS



(d) LS Largest Difference

Figure 4.29: The key randomised (LS) profiles. These profiles correspond to the key results in table 4.17.

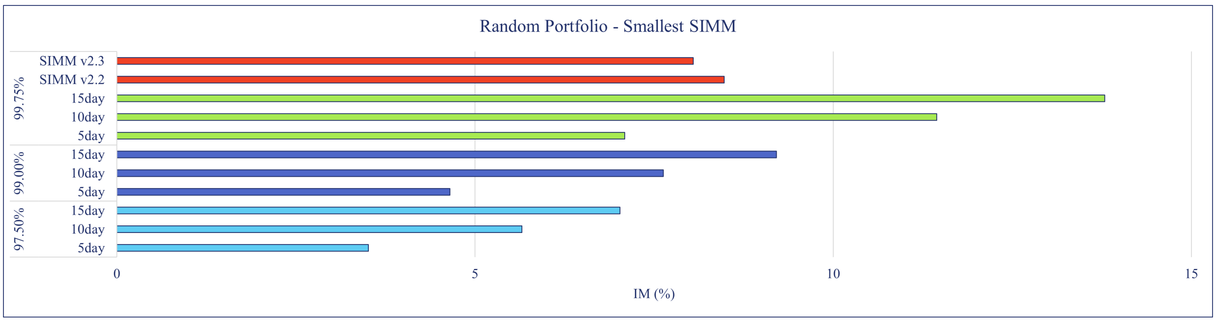


Figure 4.30: Horizontal bar plot showing the results of the portfolio, from the randomised portfolio (LS) comparisons, that obtained the **smallest SIMM** version 2.3 estimate.

The profiles that result in the largest SIMM and largest FHS appear to be very different in figure 4.29. The main reason the profile in 4.29b is the highest SIMM estimate is because it has almost all positive weights. The SIMM here is 74.28% which is comparable to the results from the flat comparison before. The SIMM would be exactly the same here if all these PV01 values had been simulated as negative instead, it just happens that this particular set of simulations resulted in a profile that looked like this. The profile that results in the largest 10-day 99% FHS in this case happens to be a portfolio with mostly negative weights in 4.29c. The relevant FHS estimate here is 42.85% compared to SIMM version 2.3's 62.37%. Figures 4.31 and 4.32 show how the SIMM comfortably covers the risks in these two cases.

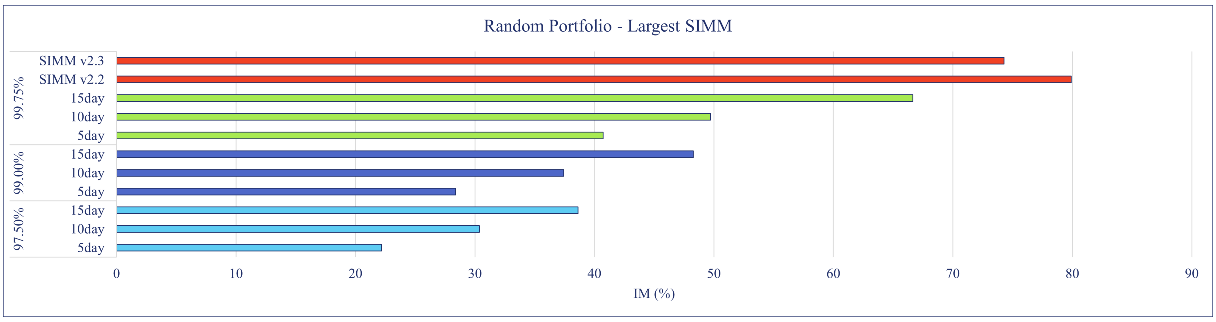


Figure 4.31: Horizontal bar plot showing the results of the portfolio, from the randomised portfolio (LS) comparisons, that obtained the **largest SIMM** version 2.3 estimate.

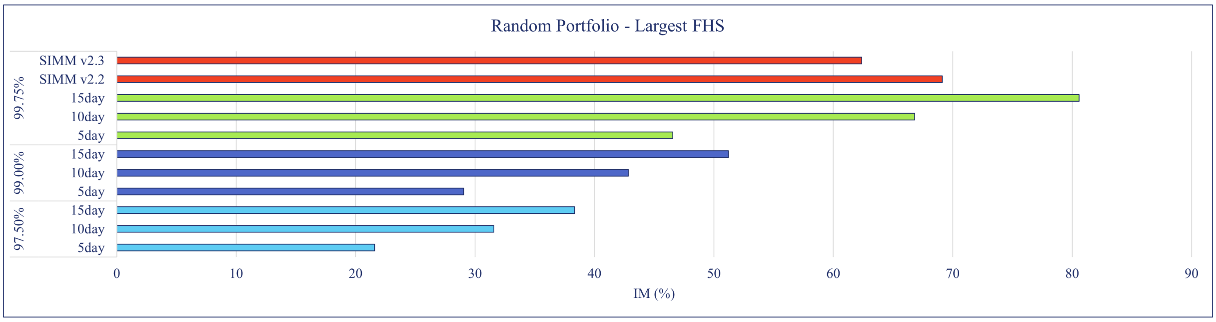


Figure 4.32: Horizontal bar plot showing the results of the portfolio, from the randomised portfolio (LS) comparisons, that obtained the **largest FHS** ES estimate at the 10-day 99% calibration.

The most remarkable result so far is the relative largest difference of table 4.17. Note that in tables 4.15 and 4.16 the largest relative difference would have coincided with the largest FHS portfolio in both cases. Looking at the largest relative difference (rather than absolute difference as is the case with the LO and SO comparisons) would show exactly for which portfolio in this analysis the SIMM would mispecify the tail risk the most at the 10-day 99% calibration.

In figure 4.33 one sees the results of the portfolio with the most breaches of SIMM out of all the portfolios considered so far. Here the entire 99.75% and 99% level surpass SIMM at all the h-day calibrations shown, as well as at the 15-day 97.5% level. The SIMM version 2.3 estimate of 13.93% is well below the 10-day 99% FHS ES estimate of 19.57%, in relative terms. Despite this being the largest 10-day 99% estimate in comparison to SIMM, the IM requirements are still low compared to other portfolios in absolute terms.

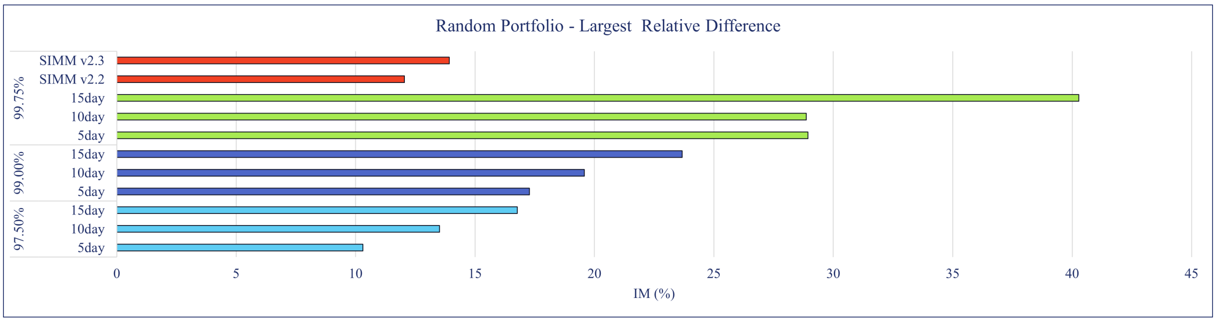


Figure 4.33: LS Largest Relative Difference Horizontal bar plot showing the results of the portfolio, from the randomised portfolio (LS) comparisons, that obtained the **largest relative difference** between the ES estimate at the 10-day 99% calibration and the SIMM version 2.3 estimate.

The profile shown in figure 4.29d has a shape that has not been stressed in previous analysis. The largest negative exposures is on the 1Y tenor and the largest positive exposure is on the 3Y tenor, with more positive exposures on the short end and negative exposures for longer tenors. This profile shows the maximum risk exposure that SIMM does not cover at the required risk level. It is profiles that look like this one that combine the correlation and skweness effects, discussed throughout these analysis, into a situation where SIMM's broad calibration leaves a small gap in risk coverage.

The analysis in this section brings together the results obtained before and utilises these findings to understand and explain the level of risks that various portfolios have at various margin periods of risk. SIMM covers particular portfolios very well at the required risk levels, but due to the broad calibration of SIMM the very calibrations that can be seen as strengths for SIMM in certain situations plays against it in other situations, particularly with the LS profiles.

4.5 MODEL VALIDATION RESULTS

Here the model validation results are given for the VaR model, consistent with the ES model that gave the results, at the 5-day 99% level. The statistical results as well as figures are presented to summarise the findings. The results here confirm that the VaR model is accurate, therefore the results provided in this chapter can be trusted to a large extent.

Figure 4.34 summarises the results of the backtest described in section 3.6. It contains the 5-day 99% VaR and the SIMM version 2.2. and 2.3 as a percentage of the absolute PV01 exposure of the portfolio. The dates given on the horizontal axis are the start dates for the out-of-sample test samples. For example the first date 2019-08-08 refers to the sample period starting 2019-08-08 and ending 2019-08-16, which represents 5 trading days in the overall sample[2].

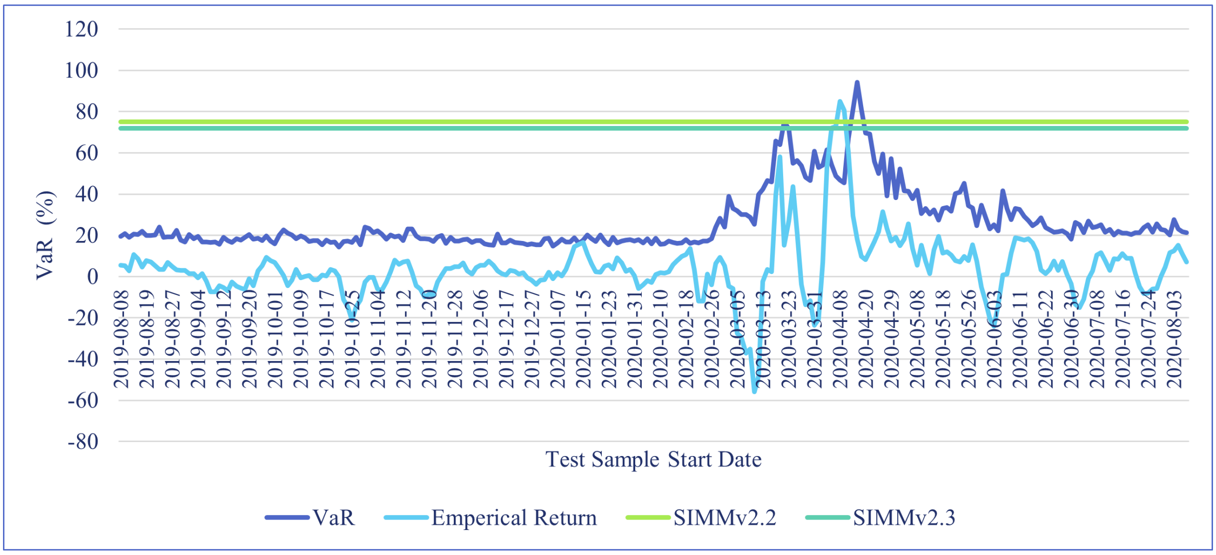


Figure 4.34: A plot showing the validation results. The overlapping 5-day empirical absolute loss as well as the corresponding 5-day 99% VaR estimate at each of the 250 days in the backtest are shown. The empirical returns exceed the VaR estimate only four times, indicating that the model passes the backtest. The SIMM version 2.2 and 2.3 estimates are also shown which are exceeded around the same time as the VaR model. The values in the graph are standardised to relative terms using (3.2).

The VaR model only generates four exceedances over the 250 day test period, which is within the confidence bands shown in section 2.5 of $\left(-0.5834,\ 5.5834\right)$. Thus the hypothesis is accepted at the 95% confidence level, hence the VaR model is adequate.

It is visually evident that the empirical returns are autocorrelated. Since the empirical estimates use overlapping samples, one large single return can persists in the estimates for five days. This means that the standard errors would need to be enlarged and the confidence levels widened for

[2]Note again that the empirical returns here are created using overlapping samples.

the hypothesis test to account for this feature. Despite this, however, the VaR model achieves the recommended target.

If the number of exceedances are compared to the regulatory standard backtest recommendations, this VaR model falls within the so-called 'green-zone' which is a model with four or less exceedances over a 1-year test period. The number of exceedances appear to be clustered starting 2020-04-06, with four consecutive exceedances of the empirical return estimate. This can be seen as a feature of using overlapping samples for comparison, where the presumption is that it would be less if using a longer back-test period with non-overlapping samples.

It is clear from figure 4.34 that the FHS model is able to capture the volatility of the market and adapt to the necessary levels, especially during stress periods. The increase in VaR estimates from the periods around March to June 2020 shows that the chosen model is able to express the correct risk levels throughout time. For those concerned that this model may promote procyclicality issues, one can always use a smoothing parameter as mentioned in 2.3[3].

It can also be seen that the empirical returns breaches both the SIMM estimate during the same period that it breeches the 99% VaR estimate. The SIMM levels remain unchanged, as the backtest assumes constant rebalancing of the portfolio. This can be seen as a great advantage for SIMM as it does not suffer from procyclicality in order to afford a great sense of risk coverage. The VaR estimate at the end of the sample period shown here is directly proportional to the volatility level used to initiate the estimates in this analysis. These volatilities appear to be slightly higher than the average volatilities of the tranquil period, but are not too heavily inflated, as in the March-June stress period. Thus the analysis conducted here is not necessarily biased toward either a tranquil nor stressed market regime.

What is evident from all the analysis is that the SIMM level is often much higher than the estimated risk level at the 99% level. This can also be seen from figure 4.34, where the SIMM is consistently higher than the VaR estimates[4]. This is also true for most of the 10-day 99% ES estimates that are the focus of the comparisons conducted in this chapter.

[3]This would require either an ad-hoc choice of smoothing parameter that depends on the risk appetite of any given CCP, or an optimal choice can be obtained through extensive simulation or bootstrap procedures, beyond the scope of this paper.

[4]Note that the ES estimates in all these cases would be higher than the corresponding VaR.

The VaR model is shown to be accurate with the backtest, despite the modifications that would make it harder to pass the test. Other useful insights, regarding the models in the context of time, are also gained in this section, albeit a brief section. The validation procedure and the figures shown here also add some transparency to how the FHS model would perform over time, where the SIMM values are included so that one can see how they compare with the empirical returns over this sample period.

4.6 SUMMARY

This chapter contains the results for the analysis described in chapter 3, where the main aim is to break down the IM risk exposure for various portfolios in order to assess delta risk IM appropriateness in the SA OTC IRS market. The findings in this chapter show how the SIMM and the FHS model differ. The SIMM is in most cases sufficient to cover the risks at the required 10-day 99% risk level, but some anomalies are found. The results are presented so that any strange findings can be explained.

It is clear from the analysis in section 4.2, where the SIMM risk weights are analysed, that the return distributions for the tenors are not symmetric. For long exposures (positive PV01) the short-term tenor distributions (2W - 6M) showed to have larger tail risk, whereas the tail risk is higher for short exposures at the long-term tenors (1Y - 30Y). Some of the tenors simulated distributions and volatility process are investigated to gain insight into the results for the FHS model and to uncover the sources of risk in the coverage of SIMM.

The standardised comparisons of section 4.3 show some very informative results. The skewness in the distributions from the tenor comparison plays a major role on the results in this section. The exponential decreasing LO and cosine decreasing LS profiles both showed to breach their respective SIMM version 2.3 estimates at the 10-day 99% level. Both are due to the risks of the REC side of the 2W rate which is still volatile in the current market. The FHS model implies different correlations and risk weights to the SIMM model, which presents some further weaknesses when conducting a randomised comparison.

The random comparisons allow for inference on the most risky portfolios, meaning the portfolios that SIMM may not adequately cover. The trend that LO and SO exposures behave differently is repeated here, as in all of the analysis, which can be confirmed with the difference in the shapes of the key profiles. The SIMM is able to cover the risks for most of the profiles here, except some of the LS profiles. The profile LS index 239 profile in particular to show the greatest shortfall of SIMM to the FHS model throughout the analysis, by exploiting the broad calibration weakness of SIMM.

The validation procedure confirmed that the 5-day VaR model is accurate at the 99% level, despite the modifications that would make it more difficult to pass. It can also be seen that the relative volatility level that is used to initialise the results of the FHS algorithm strikes balance between tranquil and stressed volatility regimes.

CHAPTER 5

CONCLUSION AND AREAS FOR FURTHER RESEARCH

5.1 INTRODUCTION

This chapter presents the findings of this report and concludes this research. Section 5.2 summarises the findings from chapter 4 and discusses the implications thereof in further depth. Recommendations are given on how to utilise the results and discoveries for real-world application. Recommendations are also given on how to utilise the methodological framework to conduct further research. Section 5.3 describes the various other potential areas for research. Recommendations are also given here with regard to improvements to the framework or variations that could answer some additional questions. The final section 5.4 ends this research by summarising this chapter and gives some concluding remarks.

5.2 FINDINGS AND RECOMMENDATIONS

The primary aim of this analysis, as laid out in chapter 3, was to analyse the margin appropriateness of the ISDA SIMM in the domestic SA IRS market. The necessary literature that was required to follow the analysis was reviewed in chapter 2. Using the FHS model for comparison was a natural choice as it can be calibrated using market data and can scale the volatilities to relevant times, much like the CCP models. Details regarding the FHS procedure as well as the SIMM calculations used in the analysis was presented in chapter 3. This chapter also describes a sequential methodology for comparing the risk weights and correlations of the SIMM with the FHS model. Chapter 4 gives the results of this methodology which show some noteworthy findings. These findings are further deliberated in this section.

It was clear from the results and displays in section 4.2 that the SIMM was able to cover the risk for isolated exposures at each of the required tenors. The only concern was the long side exposure of the 2W rate. This exposure plays a role in the results of section 4.3, where the two shortfalls of SIMM at the 10-day 99% level can be seen as a cause of this long exposure. In section 4.4, the cause of the greatest shortfall was not necessarily because of this, but rather because the random profiles, for the LS side in particular, could exploit the difference in correlations of SIMM and those implied by the FHS model. This was also largely due to the skews seen of the long side and short side exposures.

For ST exposures it was clear that the parties gaining from a present value increase in the respective rate would be more exposed than their counterparty. The opposite was the case for LT maturities, where floating rate payers are more exposed than the receivers of the floating rate. This feature was present throughout the analysis and explains the differences between the long side and short side exposures for the standardised profile comparisons and the randomised comparisons.

The SIMM was shown to be adequate in most cases at the 10-day 99% risk level, but because of the broad calibration of its risk factors and correlations there are naturally gaps where the SIMM may not be able to cover a specific portfolio. This was because the correlations in any particular market will not necessarily be the same as the SIMM correlations. Such discrepancies can be uncovered using this framework as shown in this analysis. Therefore a gap in gap risk coverage can be shown to exist in some fringe cases.

The results are also independent of the absolute size of portfolios, through standardisation. Hence the results can be applied universally to various real world portfolios. This was why much emphasis was paid to the shape of the profiles rather than the absolute exposures throughout the discussion. This allows traders and those making business decisions to compare their portfolio shapes to those shown in this analysis and determine whether the SIMM is adequate for them.

In addition to the results reported, practitioners can utilise the framework using either their own systems or this one, to perform an ongoing analysis of the appropriateness of SIMM through time. This is more beneficial to any company than the results and findings reported here alone, since many additional model choices for the FHS can be made making it more relevant to the institution's needs. Thereby an institution can monitor whether SIMM was appropriate based on their own risk standards for each trade.

This analysis combines the research presented by Barnes (2016) with regard to evaluating the SIMM and Lee and Seo (2018) for creating CCP type FHS ES models to produce novel techniques in evaluating the appropriateness of the delta risk IM coverage in the ISDA SIMM. The aims were to test the input space of the model using simple cases and gradually include more features to unravel the potential sources of risk.

5.3 AREAS FOR FURTHER RESEARCH

There are a number of variations to the presented framework that could yield additional beneficial insights. The analysis here explored the dimensions of α and h in terms of the risk assessment. Through an inclusion of a volatility floor, with various calibrations for the slack parameter, additional insight into another risk dimension can be gained. This type of analysis could for example show the SIMM risk coverage in tranquil, normal and stressed volatility regimes which would additionally inform of the margin appropriateness of SIMM.

This analysis tested the delta risk component of SIMM for the OTC IRS market in SA using a simulated methodology. The methodology can be extended sequentially by adding variations of the swap. A natural extension is to include cross-currency swaps. This can be analysed through an extension of the FHS methodology presented, whereby additional parameters of the SIMM are also included and can therefore be assessed.

The FHS methodology would work well especially for risk exposures that show curvature risks, such as swaptions or equity derivatives. The historical simulation does not require a specification of the complex correlation structure that drives the price movements of these portfolios. Therefore comparing SIMM's SBA estimates to a historically simulated risk measure for these additional product types could unveil more of the margin appropriateness of the ISDA SIMM.

5.4 SUMMARY AND CONCLUSION

The SIMM allows for appropriate margins in most cases, but due to the broad nature of the parameters used in the SIMM there are certain portfolios, especially those with a mixture of positive and negative exposures to the swap curve, that may be exposed under the SIMM for a 10-day MPR. The standardisation of the results allows for the shapes of the profiles to determine the risks, therefore the findings can be universally applied. It is recommended that this type of analysis be done through time so as to remain relevant to an institutions current risks. Further research can be conducted along the lines of this framework for either additional types of swaps or adding other product types as recommended in section 5.3. Variations of this framework can also give additional insights into the risks an institution may be facing in terms of their gap risk coverage.

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Appendix: Python Code

```
# Import the required packages
import numpy as np # vectorised operations
import matplotlib.pyplot as plt # plotting functionality
import pandas as pd # matrix/data frame manipulation
import datetime # manages time variables
from arch import arch_model # for GARCH estimation
import random # for setting seeds
from math import sqrt # square root
from math import floor # floor function

# Import Daily Absolute Returns of the South African Swaps Index Curve
returns = pd.read_excel("returns.xlsx")
# Heading Names #Tenors
tenors =  ['2W', '1M', '3M', '6M', '1Y', '2Y', '3Y', '5Y', '10Y', '15Y', '20Y',
    '30Y']

def garch_est(data, headings, plot_opt = False):
    #data is a dataframe with the column headings of the tenors
    #
    # Initialise output matrices:
    out_mat = pd.DataFrame(data = None, columns = headings, index = ['omega',
        'alpha', 'beta', 'scale'])
    out_vol = pd.DataFrame(data = None, columns = headings)
    for tenor in headings: # repeat for each of the tenors
        # Zero-Mean GARCH(1,1) model
        model = arch_model(np.array(data[tenor]), vol = 'Garch', p = 1, q = 1, o
            = 0, dist = 'Normal', rescale = True)
        model_fit = model.fit(disp = 'off') # setting disp = 'on') shows
            convergence results
        #
        # Extract the paramters
        omega = model_fit.params['omega']
        alpha = model_fit.params['alpha[1]'] # shock
        beta  = model_fit.params['beta[1]'] # persistence
        scale = model_fit.scale # scale -> 1 in any case for all analysis
        #
        # store the daily volaitilties of the tenor
        out_vol[tenor] = model_fit._volatility/scale # rescale the volatility
        # store the parameters
        out_mat[tenor] = [omega, alpha, beta, scale]
        #
        if plot_opt:
            # if selected, function outputs a plot of the annualised daily
                volatilities of each rate
            model_fit.plot(annualize = 'D')#
    return out_mat, out_vol # tuple output

# Obtain the parameters and estimated volatilities for the tenor rates
param = garch_est(data = returns, headings = tenors, plot_opt = False)

# Function that standardises returns by diving their returns by the obtained
    volatility estimates
def standard_ret(data, vols):
    e_mat = data.reset_index(drop = True)
    vols = vols.reset_index(drop = True)
    return e_mat/vols # scales returns

e_ret = standard_ret(data = returns, vols = param[1])

# Function that performs the actual simulations
def fhs(data, r_0, vol_0, parameters, h = 10, N = 100):
    # function performs filtered historical simulation
    # data is a data frame of the form chronological daily bp returns
    # r_0 initial risk factor returns vector
```

```
    # vol_0 initial volatility estimates
    # h = number of days in the multi-step procedure # MPR
    # N = number of times the simulation runs # 10 000
    # parameters of the form index: omega, alpha, beta, scale
    # Output is in BP returns
    #
    # Initialise Output Vector:
    out_mat = pd.DataFrame(data = None)
    # create a loop for each iteration
    for it in range(0, N):
        # initialise data frame to store simulated returns
        r = pd.DataFrame(data = None)
        # Random Sample of size h (represents h random draws from the
            standardised residuals)
        sample = random.sample(list(range(0,len(data))), h)
        # Create First Volatility Estimate  # Note this does all 12 tenors at once
        vol_i = parameters.loc['omega', :] + parameters.loc['alpha',
            :]*np.power(r_0*parameters.loc['scale', :], 2) +
            parameters.loc['beta', :]*np.power(vol_0*parameters.loc['scale', :], 2)
        vol_i = vol_i.apply(sqrt)/parameters.loc['scale', :]
        # Create First Return Estimate
        r[0] = data.iloc[sample[0], :]*vol_i

        # Perform Multi-step procedure
        for i in range(1, h):
            vol_i = parameters.loc['omega', :] + parameters.loc['alpha',
                :]*np.power(r[i-1]*parameters.loc['scale', :],2) +
                parameters.loc['beta', :]*np.power(vol_i*parameters.loc['scale',
                :], 2)
            vol_i = vol_i.apply(sqrt)/parameters.loc['scale', :] # scale correctly
            # store daily ith return
            r[i] = data.iloc[sample[i], :]*vol_i # create heteroscedastic
                dependence
        ret = r.apply(axis = 1, func = np.sum) #sum over the h day returns to get
            h-day return estimate
        out_mat[it] = ret
    return out_mat

# Obtain Initialisation estimates
r_0 = returns.iloc[-1, :] #1st return to initialise var estimate
vol_0 =  param[1].iloc[-1, :] #1st volatility used for scaling

# Perform FHS Procedure # Note this process takes some time
# 5-day Simulations
random.seed(101) #Set seeds to reproduce results
sims_h5 = fhs(data = e_ret, r_0 = r_0, vol_0 = vol_0, parameters = param[0], h =
    5, N = 10000) # runs 10 000 5-day simulations
sims_h5.to_excel("simsh5.xlsx") # export the simulations
# 10-day Simulations
random.seed(101)
sims_h10 = fhs(data = e_ret, r_0 = r_0, vol_0 = vol_0, parameters = param[0], h =
    10, N = 10000)
sims_h10.to_excel("simsh10.xlsx")
# 15-day Simulations
random.seed(101)
sims_h15 = fhs(data = e_ret, r_0 = r_0, vol_0 = vol_0, parameters = param[0], h =
    15, N = 10000)
sims_h15.to_excel("simsh15.xlsx")

# Function that determines a distributions for a given input, theta, and outputs
    a VaR and corresponding ES estimate
def IM_calc_fhs(theta, sims, alpha):
    # function that determines the IM based on FHS VaR and ES
    # theta is a 2d np.array representing the PV01 sensitivities
    sims = np.array(sims) # convert the simulations into an np array
```

```python
    dist = theta.dot(sims) # apply dot product to the simulation matrix
    # this gives a distribution for the portfolio

    # Obtain alpha h-day VaR and ES estimates
    VaR = -np.quantile(dist, 1-alpha) # VaR as per the definition
    ES = -np.mean(dist[dist<-VaR]) # Expected Shortfall given the VaR level has exceeded
    return VaR, ES

# simpler function than the one above: can be used with an already created distribution
def var_calc(dist, alpha):
    # simpler var calc: takes already created distribution
    dist = np.array(dist) # ensure that it is an np array
    VaR = -np.quantile(dist, 1-alpha) #
    ES = -np.mean(dist[dist<-VaR]) #
    return VaR, ES

# quick SIMM Calculator for Delta IR Risk
def quick_k(theta, rw, corr):
    # Function that calculates Delta Risk for SIMM IM
    # Excludes CR factor
    # theta is PV01 sensitivities
    # rw is a vector of the Risk Weights
    # corr is the correlation matrix
        # ensure inputs are np array:
    theta = np.array(theta)
    rw = np.array(rw)
    corr = np.array(corr)
    ws = theta*rw # weighted sensitivities
    k = np.sqrt(ws.transpose().dot(corr).dot(ws)) # final K calculation (single party exposure)
    return k

# SIMM Version 2.2 and 2.3 Risk Weights and Correlations
# SIMM Version 2.2
bucket1_2 = (116,106,94,71,59,52,49,51,51,51,54,62) # regular currencies
bucket3_2 = (85,80,79,86,97,102,104,102,103,99,99,100) # risk bucket for high volatility currencies
correlations_2 = pd.read_csv("correlations2019.csv", header = None) # v2.2 correlations
# SIMM Version 2.3
bucket1_3 = (114,107,95,71,56,53,50,51,53,50,54,63) # regular currencies
bucket3_3 = (103,96,84,84,89,87,90,89,90,99,100,96) # high volatility currencies
correlations_3 = pd.read_csv("correlations2020.csv", header = None) # v2.3 correlations

# Function that produces Tables of VaR estimates for the comparison
def TC(sims5 = sims_h5, sims10 = sims_h10, sims15 = sims_h15, alphas = (0.975, 0.99, 0.9975), tenors = tenors):
    # creates a table that displays the 5-day, 10 day and 15day var and es estimates for a given CL
    # takes in the created simulations
    # alphas are the VaR significance levels required
    # initialise the output matrix
    columns = pd.MultiIndex.from_product([['Rec', 'Pay'],['0.975', '0.99', '0.9975'], ['5day','10day', '15day', 'simm_2', 'simm_2UK', 'simm_3', 'simm_3UK']])
    out = pd.DataFrame(data = None, columns = columns, index = tenors)

    theta_rec = np.full((len(sims5), 1), 1)  #
    theta_pay = np.full((len(sims5), 1), -1)
    var5_dist_rec, var10_dist_rec, var15_dist_rec =  (theta_rec)*sims5, (theta_rec)*sims10, (theta_rec)*sims15
    var5_dist_pay, var10_dist_pay, var15_dist_pay = (theta_pay)*sims5, (theta_pay)*sims10, (theta_pay)*sims15
```

```
    # Create data frames to store the SIMM values
    simm_2 = pd.DataFrame(data = None, columns = tenors)
    simm_2UK = pd.DataFrame(data = None, columns = tenors)
    simm_3 = pd.DataFrame(data = None, columns = tenors)
    simm_3UK = pd.DataFrame(data = None, columns = tenors)
    for i, tenor in enumerate(tenors):
        theta_vec = np.zeros(len(tenors)) #
        theta_vec[i] = 1
        #SIMM v2.2 SA bucket
        simm_2.loc[0, tenor] = quick_k(theta_vec, rw = bucket3_2, corr =
            correlations_2)
        # SIMM v2.3 SA bucket
        simm_3.loc[0, tenor] = quick_k(theta_vec, rw = bucket3_3, corr =
            correlations_3)
        # SIMM v2.2 UK Bucket
        simm_2UK.loc[0, tenor]  = quick_k(theta_vec, rw = bucket1_2, corr =
            correlations_2)
        # SIMM v2.3 UK Bucket
        simm_3UK.loc[0, tenor]  = quick_k(theta_vec, rw = bucket1_3, corr =
            correlations_3)
    for i, tenor in enumerate(tenors):
        for alpha in alphas: # get the
            # REC
            es5_rec = var_calc(var5_dist_rec.iloc[i, :], alpha = alpha)[1]
            es10_rec = var_calc(var10_dist_rec.iloc[i, :], alpha = alpha)[1]
            es15_rec = var_calc(var15_dist_rec.iloc[i, :], alpha = alpha)[1]
            out.loc[tenor, ('Rec', str(alpha))] = [es5_rec, es10_rec, es15_rec,
                simm_2[tenor][0], simm_2UK[tenor][0], simm_3[tenor][0],
                simm_3UK[tenor][0]]
            # PAY
            es5_pay = var_calc(var5_dist_pay.iloc[i, :], alpha = alpha)[1]
            es10_pay = var_calc(var10_dist_pay.iloc[i, :], alpha = alpha)[1]
            es15_pay = var_calc(var15_dist_pay.iloc[i, :], alpha = alpha)[1]
            out.loc[tenor, ('Pay', str(alpha))] = [es5_pay, es10_pay, es15_pay,
                simm_2[tenor][0], simm_2UK[tenor][0], simm_3[tenor][0],
                simm_3UK[tenor][0]]
    return out # outputs a multi-index matrix containing the results
tc_results = TC()
tc_results.to_excel("tc.xlsx")

# Import the PV01 Vectors -- these were created in Excel
PV01_mat = pd.read_excel("scvals.xlsx", index_col = [0,1,2], header = 0).dropna()

# Function that performs the analysis
shapes = ['Linear', 'SINE', 'COSINE', 'EXP', 'ALT', 'SL'] # shapes used in this
    analysis # Note that the flat comparisons are done separately
types = ['LO', 'SO', 'L-S']
def SC(PV_mat, sims5, sims10, sims15, alphas = (0.975, 0.99, 0.9975), shapes =
    shapes, types = types):
    # standardised Comparison
    # import the simulated distributions for h=5,10,15
    # alphas are the VaR significance levels
    # shapes is a vector of names for the shapes
    # types is a vector that specifies whether the comparison is LO, SO or LS
    # Initialise output dictionary
    out_dict = {}
    for shape in shapes:
        temp_mat = PV_mat.loc[shape]
        index = pd.MultiIndex.from_tuples(temp_mat.index)
        columns = pd.MultiIndex.from_product([['.975', '0.99',
            '0.9975'],['5day','10day', '15day', 'simm_2', 'simm_2UK', 'simm_3',
            'simm_3UK']]) # creates columns for the multi-index output matrices
        out_mat = pd.DataFrame(data = None, index = index, columns =columns)
        indexer = 0
```

```
        for t in types: # perform the analysis for each type
            for d in range(0, len(temp_mat.loc[t])):
                for j, alpha in enumerate(alphas):
                    out = pd.DataFrame(data = None)
                    es5_temp = IM_calc_fhs(temp_mat.loc[t].iloc[d], sims = sims5, alpha = alpha)[1]
                    es10_temp = IM_calc_fhs(temp_mat.loc[t].iloc[d], sims = sims10, alpha = alpha)[1]
                    es15_temp = IM_calc_fhs(temp_mat.loc[t].iloc[d], sims = sims15, alpha = alpha)[1]
                    simm2_temp =  quick_k(temp_mat.loc[t].iloc[d], rw = bucket3_2, corr = correlations_2)
                    simm2UK_temp = quick_k(temp_mat.loc[t].iloc[d], rw = bucket1_2, corr = correlations_2)
                    simm3_temp =  quick_k(temp_mat.loc[t].iloc[d], rw = bucket3_3, corr = correlations_3)
                    simm3UK_temp = quick_k(temp_mat.loc[t].iloc[d], rw = bucket1_3, corr = correlations_3)
                    # Store the values in the output matrices
                    out[alpha] = [es5_temp, es10_temp, es15_temp, simm2_temp, simm2cr_temp, simm3_temp, simm3cr_temp]
                    out_mat.iloc[indexer,(0 + j*7)] = es5_temp
                    out_mat.iloc[indexer,(1 + j*7)] = es10_temp
                    out_mat.iloc[indexer,(2 + j*7)] = es15_temp
                    out_mat.iloc[indexer,(3 + j*7)] = simm2_temp
                    out_mat.iloc[indexer,(4 + j*7)] = simm2UK_temp
                    out_mat.iloc[indexer,(5 + j*7)] = simm3_temp
                    out_mat.iloc[indexer,(6 + j*7)] = simm3UK_temp
                indexer = indexer + 1
        out_dict[shape] = out_mat
    return out_dict # outputs a dictionary indexed by the shape name that contains a multi-index matrix of the results

# obtain results
sc_results = SC(PV_mat = PV01_mat, sims5 = sims_h5, sims10 = sims_h10, sims15 = sims_h15)

# Export
from openpyxl import load_workbook
pd.DataFrame().to_excel("sc.xlsx")
workbook1 = load_workbook("sc.xlsx")

writer = pd.ExcelWriter("sc.xlsx", engine = 'openpyxl')
writer.book = workbook1
for shape in results.keys():
    out = pd.DataFrame(results[shape])
    out.to_excel(writer, sheet_name = '%s'%shape, index = True, startrow = 1, startcol = 1)
    #tick = tick + 1
    #new_file.to_excel(writer, sheet_name='Shee1', index = False, startrow = 2, startcol = 1)

writer.save()
writer.close()

# Flat comparisons
flats = SC_flat(PV_mat = PV01_mat, sims5 = sims_h5, sims10 = sims_h10, sims15 = sims_h15, shapes = 'FLS'], types = ['LO', 'SO'])
# Export
pd.DataFrame(flats['FLS']).to_excel('sc_flat.xlsx')

# Create Randomised Portfolios
random.seed(101) # set seed for reproducibility
# Long - short Profiles
```

```
# Generate 1000 random portfolios
profiles_ls = pd.DataFrame(data = None, columns = tenors, index = range(0,1000))
for i in range(0,1000):
    profiles_ls.iloc[i, :] = np.random.normal(0, 1, len(tenors))

random.seed(102) #
# Long Only Profiles
# Generate 1000 random portfolios
profiles_l = pd.DataFrame(data = None, columns = tenors, index = range(0,1000))
for i in range(0,1000):
    profiles_l.iloc[i, :] = abs(np.random.normal(0, 1, len(tenors)))

random.seed(103) #
# Short Only Profiles
# Generate 1000 random portfolios
profiles_s = pd.DataFrame(data = None, columns = tenors, index = range(0,1000))
for i in range(0,1000):
    profiles_s.iloc[i, :] = -abs(np.random.normal(0, 1, len(tenors)))

# Export these profiles
profiles_ls.to_excel("profiles_ls.xlsx")
profiles_l.to_excel("profiles_l.xlsx")
profiles_s.to_excel("profiles_s.xlsx")

# function that performs the randomised comparison analysis
def RC(PV_mat, sims5 = sims_h5, sims10 = sims_h10, sims15 = sims_h15, alphas = (0.975, 0.99, 0.9975), N = 1000):
    # Random Comparison
    # takes the simulated distributions as input
    # performs the output for various VaR significance levels alpha
    columns = pd.MultiIndex.from_product([['0.975', '0.99', '0.9975'], ['5day','10day', '15day', 'simm_2', 'simm_2UK','simm_3', 'simm_3UK']])
    out = pd.DataFrame(data = None, columns = columns, index = range(0, N))
    for i in range(0, 1000):
        for alpha in alphas:
            es5 = IM_calc_fhs(PV_mat.iloc[i, :], sims = sims5, alpha = alpha)[1]
            es10 = IM_calc_fhs(PV_mat.iloc[i, :], sims = sims10, alpha = alpha)[1]
            es15 = IM_calc_fhs(PV_mat.iloc[i, :], sims = sims15, alpha = alpha)[1]
            simm_2 =  quick_k(PV_mat.iloc[i, :], rw = bucket3_2, corr = correlations_2)
            simm_2UK = quick_k(PV_mat.iloc[i, :], rw = bucket1_2, corr = correlations_2)
            simm_3 =  quick_k(PV_mat.iloc[i, :], rw = bucket3_3, corr = correlations_3)
            simm_3UK = quick_k(PV_mat.iloc[i, :], rw = bucket1_3, corr = correlations_3)
            out.loc[i, str(alpha)] = [es5, es10, es15, simm_2, simm_2UK, simm_3, simm_3UK]
    return out

# Obtain Results
results_ls = RC(PV_mat = profiles_ls)
results_l = RC(PV_mat = profiles_l)
results_s = RC(PV_mat = profiles_s)
# Export Results
results_ls.to_excel("rc_ls.xlsx")
results_l.to_excel("rc_l.xlsx")
results_s.to_excel("rc_s.xlsx")

# Create a function that creates the dates used for indexing when performing validation
def index_dates(data = returns, h = 10, overlapping = True, fixed_size = 250):
    # func creates data frame of indexed dates
    # can be overlapping or non-overlapping
```

```
    start_date = data.index.values[0]
    end_date = data.index.values[-1]
    if overlapping: # if overlapping samples are to be created
        total_size =  len(data) - fixed_size - h
        out = pd.DataFrame(data = None, columns = ['EstStart', 'EstEnd', 'TestStart', 'TestEnd' ], index = range(0, total_size))
        for i in range(0, total_size):
            out.loc[i, 'EstStart'] = data.index.values[i] # Start date for GARCH estimation and historical sample
            out.loc[i, 'EstEnd'] = data.index.values[i + fixed_size]# End date for GARCH estimation and historical sample
            out.loc[i, 'TestStart'] = data.index.values[i + fixed_size + 1] # first day of the empirical test sample
            out.loc[i, 'TestEnd'] = data.index.values[i + fixed_size + h] # last day of the h-day empirical sample
    else: # if non-overlapping samples are needed
        total_size =  floor(((len(data) - (fixed_size + h))/h)) #
        out = pd.DataFrame(data = None, columns = ['EstStart', 'EstEnd', 'TestStart', 'TestEnd' ], index = range(0, total_size))
        for i in range(0, total_size):
            out.loc[i, 'EstStart'] = data.index.values[i*h]
            out.loc[i, 'EstEnd'] = data.index.values[i*h + fixed_size]
            out.loc[i, 'TestStart'] = data.index.values[i*h + fixed_size + 1]
            out.loc[i, 'TestEnd'] = data.index.values[i*h + fixed_size + h]
    return out # output is a 4 column matrix of dates

# Create a function that estimates the empirical h-day returns
def empirical_returns(theta = theta, data = returns, indexDates = index_dates()):
    # function that computes actual empirical h-day returns given by IndexDates Test Dates
    out = {}
    for i in range(0, len(indexDates)):
        #print(data.loc[indexDates.loc[i, 'TestStart']:indexDates.loc[i, 'TestEnd'], :])
        ret = data.loc[indexDates.loc[i, 'TestStart']:indexDates.loc[i, 'TestEnd'], :].apply(theta.dot, axis = 1)
        #print(ret)
        ret = -np.sum(ret)
        #print(ret)
        #print(-theta.dot(data.loc[indexDates.loc[i, 'TestStart']:indexDates.loc[i, 'TestEnd'], :].apply(np.sum)))
        out[i] = ret
    return out
# Function that peforms the validation procedure
def fhs_val(theta = theta, data = returns, indexDates = index_dates(), h = 5, N = 1000, alpha = 0.975):
    # func evaluates and computes fhs_val for a given alpha level.
    # theta: the Trial PV01 Vector
    # data are the returns
    # index dates matrix # make sure to line up with h
    # N : number of simulations to run for estimation
    # alpha is the confidence level for VaR Calculation
    # initialise dictionaries
    param = {} # Stores GARCH paramters # keys are est start date
    vols = {} # Stores GARCH Volatility Estimates
    simms = {} # Stores FHS Simulations
    VaR = {}
    ES = {}
    for i in range(0, len(indexDates)):
        print(i)
        data_temp = data.loc[indexDates.loc[i, 'EstStart']:indexDates.loc[i, 'EstEnd'], :]
        # Garch Estimation
        gparam = garch_est(data = data_temp, plot_opt = False) # stores in a
```

```
            tuple the param and vol ests
        param[i] = gparam[0]
        vols[i] = gparam[1]
        # FHS Simulation
        e_mat = standard_ret(data = data_temp, vols = gparam[1]) # standardise
            returns
        r_0 = data_temp.iloc[-1, :] # last return of sample
        vol_0 = gparam[1].iloc[-1, :] # last vol estimate of sample
        fhsSim = fhs(data = e_mat, r_0 = r_0, vol_0 = vol_0, parameters =
            gparam[0], h = h, N = N) # simulations matrix
        simms[i] = fhsSim #stores the SIMM
       # VaR and ES Calculation
        VaR[i], ES[i] = IM_calc_fhs(theta = theta, sims = fhsSim, alpha = alpha)
    h_ret =  emperical_returns(theta = theta, data = data, indexDates =
        indexDates)
    return VaR, ES, h_ret, param, simms # outputs a tuple of the various
        componenets
# run the validation procedure
# Note that this may take some time
random.seed(101)
fhs_val_h10_99 = fhs_val(theta = theta, data = returns, indexDates =
    indexDates_h10, h = 10, N = 1000, alpha = 0.99)
# Extract the vital information
compare = pd.DataFrame.from_dict(fhs_val_h10_99[0], orient = 'index')
compare = compare.merge(pd.DataFrame.from_dict(h10_ret, orient = 'index'),
    left_index = True, right_index = True)
# Export the results
compare.to_excel("compare_h10_99.xlsx")
```